Development of a data analytics-driven information system for instant, temporary personalised discount offers

by

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Declaration

By submitting this thesis electronically, I declare that the entirety of the work contained therein is my own, original work, that I am the sole author thereof (save to the extent explicitly otherwise stated), that reproduction and publication thereof by Stellenbosch University will not infringe any third party rights and that I have not previously in its entirety or in part submitted it for obtaining any qualification.

Date: April 2019

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To my USMA friends, who walked this path with me. Thank you for all the support, tips and memories. Then to my other friends, who did not always understand what I meant, but encouraged me regardless.

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"Be fearless in the pursuit of what sets your soul on fire." – Jennifer Lee

Abstract

Enterprises have started including the targeting of customers with personalised discount offers in their business strategies in order to seek a competitive advantage over their peers. This innovation has been made possible by the integration of knowledge and new technology such as data analytics, mobile- and cloud computing and the internet-of-things. Along with these digital technologies, the emphasis on customer experience became the distinguishing factor amongst retail outlets.

A novel approach is presented in this study to create personalised discount offers during a customer's visit to one of many participating retail outlets. It focuses on the individual customer's purchasing history, which makes it different from the loyalty programmes that are currently in use.

A simulator is developed to create pseudo-customer data containing purchasing behaviour, whereafter a demonstrator is developed which provides a holistic view of the customer's behaviour in retail outlets. The demonstrator creates instant, temporary personalised discount offers based on the purchasing tendencies of that customer across various retail outlets. The model illustrates the utilisation of customer behavioural data to identify unique cross-selling and upselling opportunities to ultimately improve customer experience.

The cross-selling and upselling creates opportunities for alternative revenue streams and this study provides a business case to display the business value of this system.

Opsomming

Ondernemings het begin om kliënte te teiken deur persoonlike afslagaanbiedings in hul sakestrategieë in te sluit ten einde 'n mededingende voordeel oor hul eweknieë te soek. Hierdie innovasie is moontlik gemaak deur die integrasie van kennis en nuwe tegnologie soos data-analise, mobiele- en wolkrekenaars en die internet-van-dinge. Saam met hierdie digitale tegnologie het die klem op kliënte-ervaring die onderskeidende faktor onder kleinhandelaars geword.

'n Nuwe benadering word in hierdie studie aangebied om persoonlike afslagaanbiedings te skep tydens 'n kliënt se besoek aan een van die deelnemende kleinhandelwinkels. Dit fokus op die individuele kliënt se aankoopgeskiedenis, wat dit anders maak as die lojaliteitsprogramme wat tans gebruik word.

'n Simulator is ontwikkel om pseudo-kliëntedata te skep wat koopsgedrag bevat, waarna 'n demonstrator ontwikkel is wat 'n holistiese oorsig gee van die kliënt se koopgedrag in kleinhandelwinkels. Die demonstrator skep onmiddellike, tydelike persoonlike afslagaanbiedings gebaseer op die aankoopneigings van daardie kliënt by verskillende winkels. Die model illustreer die gebruik van kliëntegedragdata om unieke kruis- en opverkoopsgeleenthede te identifiseer ten einde die kliënte-ervaring te verbeter.

Die kruis- en opverkope skep geleenthede vir alternatiewe inkomstestrome en hierdie studie bied 'n besigheidsgeval om die besigheidswaarde van hierdie stelsel te vertoon.

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Nomenclature

Acronyms

AAA	Arithmetical average approach
AHP	Analytic Hierarchy Process
AI	Artificial Intelligence
AL	Active Learning
APA	Acquistion Pattern Analysis
BCG	Boston Consulting Group
BDA	Big Data Analytics
CART	Classification and Regression Trees
CCSM	**C**ache-based **C**onstrained **S**equence **M**iner
CEM	Customer Experience Management
CEO	Chief Executive Officer
CLV	Customer Lifetime Value
CRISP	Cross Industry Standard Process
CRM	Customer Relationship Management
DD	Data Dictionary
EERD	Extended Entity-Relationship Diagram
FK	Foreign Key
FMCG	Fast-Moving Consumer Goods
GSP	**G**eneralised **S**equential **P**atterns
IBM	**I**ndex **B**it **M**ap
IDC	International Data Corporation

IoT	Internet of Things
KDD	Knowledge Discovery from Data
LAPIN	**LA**st **P**osition **IN**duction
LP	Last Purchase
LPIN-SPAM	**L**ast **P**osition **I**nduction **S**equential **P**attern **M**ining
MBA	Market Basket Analysis
MFS	**M**aximal **F**requent **S**equences
MS	Microsoft®
MSPS	**M**aximal **S**equential **P**atterns using **S**ampling
NPD	Next Purchase Date
ODBC	Open Database Connectivity
OPD	Object–Process Diagram
OPL	Object–Process Language
OPM	Object–Process Methodology
PDO	Personalised Discount Offer
PK	Primary Key
PPDP	Privacy-Preserving Data Publishing
PREFIXSPAN	**PREFIX**-projected **S**equential **PA**tter**N** mining
RCAA	Repurchase curve analysis approach
RE-HACKLE	**R**egular **E**xpression-**H**ighly **A**daptive **C**onstrained **L**ocal **E**xtractor
RFM	Recency, Frequency, Monetary
RL	Reinforcement Learning
SEMMA	Sample, Explore, Modify, Model and Access
SL	Supervised Learning

SLP Miner	**S**equential pattern mining with **L**ength-decreasing su**P**port
SOH	Stock on Hand
SOM	Self-Organising Maps
SPA	Sequential Pattern Analysis
SPADE	**S**equential **P**Attern **D**iscovery using **E**quivalence classes
SPAM	**S**equential **P**Attern **M**ining
SPIRIT	**S**equential **P**attern m**I**ning with **R**egular expressIon consTraints
SU	Stellenbosch University
SVM	Support Vector Machines
UL	Unsupervised Learning
WAA	Weighted average approach
WRCAA	Weighted repurchase curve analysis approach

Chapter 1

Introduction

This chapter contains a short background in order to understand where the study originated from. To ensure the study is successful, objectives are set that must be achieved in the study. These objectives are also stated in this chapter. The scope of the thesis is stated to identify the boundaries of the study and its complexity. Lastly a research methodology is given to describe how the study is executed in order to achieve the objectives.

1.1 Research background

Imagine the chaos the life of a Chief Executive Officer (CEO) would be if he forgot his phone at home on a Monday morning. All scheduled meetings would be forgotten, no online information would be available and there would be no communication with the world. This demonstrates the level of dependency on technology the world has fallen into. In the past, before the transformation to a digital world began, communication was done differently. Future events were confirmed and life did not happen at such a fast pace. But with the ever-increasing rush to achieve more and be more productive, an attitude change towards new technology became necessary.

The transformation to a more digital world is not a bad thing. The International Data Corporation (IDC) identified the so-called '3rd Platform' in 2007. This platform is built on four technology pillars, namely; mobile computing, cloud services, big data analytics and social networking (Gens, 2013). Along with this, the IDC identified the first series of innovation accelerators that depend on the 3rd Platform, where the *Internet of Things* (IoT) is one of the most promising ones. The Internet of Things can be explained as all devices that connect and communicate with each other via the internet. These range from coffee machines and alarm clocks to automated robots. This innovation makes the transfer of *Big Data* possible and with that a whole new world of innovation can exist.

As the world became more advanced in the technology spectrum, the cost of living also underwent an exponential change over time. Lately, more and more retail stores propose discount offers to their customers. One reason for this is the competitive attitude that started to exist between rival retail stores and the fact that living costs kept increasing. But now that all stores have discount offers and loyalty programmes, retail stores need a new initiative to ensure that their customer experience is superior.

The use of social media has proven to be a source of communication that reaches more and more people. It was always evident that most young adults (aged 18 to 29) use social

media. According to a survey done by Perrin (2015), the percentage of young adults using social media has increased from 12% in 2005 to 90% in 2015. The interesting fact is that the percentage of adults between the age of 30 and 49 using social media has increased by 77% from 2005 to 2015. Along with that, in 2005 the percentage of adults aged 65+ using social media was only 2%. This has increased to an astonishing 35% in 2015. It is clear that social media is being used more amongst all age groups, leading to the capture of a bigger variety of data to be analysed.

An industry partner of the industrial engineering department at Stellenbosch University used a TM Forum use case as a starting block to introduce this topic (Russom, 2016). The use case explained that a communication service provider used the location of customers to send them *personalised discount offers* (PDO). These offers are based on customers' preferences and acceptance history. The customers give the service provider permission to use their personal information and data. They also allow the receipt of advertisements and offers relevant to them.

The use case gave a generalised idea of the topic and was redefined by using the following scenario:

As a customer walks into one of many participating stores, they will receive personalised discount offers on certain items in that store. These discount offers are only valid for this specific individual at that point in time.

This can be enabled by using the *purchasing behaviour* of customers and determining which items they would be susceptible to. Using historic information, *customer profiles* can be created and personalised special offers can be determined. Along with the customer profiles, the efficiency of marketing can also be analysed and improved.

In the real world, customers must subscribe to this service and allow the company to access their buying history and location in real time. The *retail groups* and *suppliers* have to partner with the company and buy in to the service. This means that the respective entities have to subscribe and pay the company to be part of this service. The customers can download a mobile application provided by the company and use it for free. The suppliers or retail groups are able to send personalised offers to customers.

The industry partner's main focus is the customers and how they experience services. This use case was seen as an opportunity to improve customer experience, targeted marketing and ultimately generate higher revenues.

1.2 Research assignment

The industry partner wants to improve customer experience and targeted marketing by proposing personalised discounts offers to individuals at a time when customers are potentially the most susceptible to offers. This is done by creating customer profiles. A large quantity of data must be processed and analysed to create customer profiles in order to specify which offers can be made available to each individuals.

Usually, a student solves a research problem, but the nature of this topic rather requires a research assignment. What means, a formulated task must be executed instead of a problem being solved. The assignment at hand is thus to develop a *demonstrator* that creates and uses customer profiles to determine the best personalised discount offers for specific individuals in real time at one of many participating retail outlets.

1.3 Objectives

From the research assignment, two objectives were identified by the researcher to be fulfiled at the completion of the study. The two objectives are:

1. To *design* and *develop* a simulation model to create pseudo-customer data showing purchasing behaviour at various stores.

2. To *design* and *develop* a demonstrator, which uses data analytic techniques to create and analyse customer profiles and identify suitable personalised discount offers.

These objectives will be fulfilled following a predefined research methodology discussed in Section 1.5.

1.4 Scope

A simulation model is used to create data about customers' purchasing behaviour. The study focuses on *fast-moving consumer goods* (FMCG) that are purchased periodically; these typically include food items (fresh and tinned), toiletries and cleaning products. It is assumed for the purpose of this study that a *finite number of retail groups* provide the personalised discount offers. This implies that sales data are created by using a limited product list. No implementation of this study is foreseen, due to limited time.

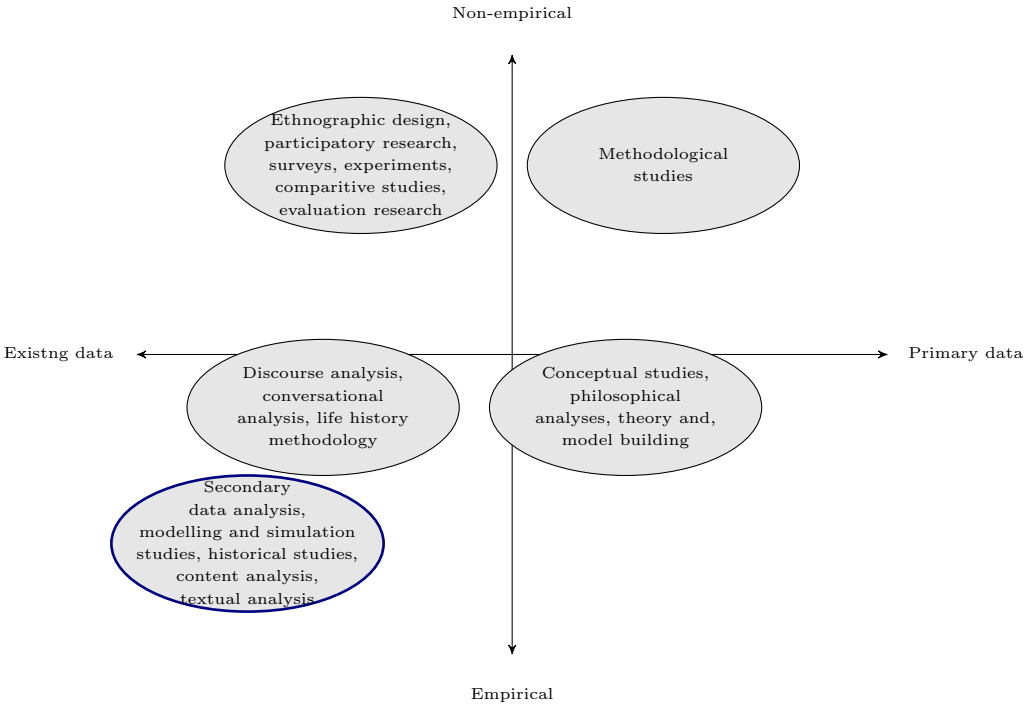


Figure 1.1: Research design map, Mouton (2001).

1.5 Research methodology

According to the research design map of Mouton (2001), a study can be classified as empirical or non-empirical using primary or existing data. This study is characterised as an empirical study using existing data as seen in Figure 1.1.

The researcher decided to follow a self-designed research methodology that was developed for this particular research assignment. The research methodology identifies four phases for this study and are visually summarised in Figure 1.2.

The first phase will consist of an in-depth literature study in order to gain knowledge regarding the different domains such as data analytics, retail and marketing. Information will be gathered from various sources and multiple platforms. The research will include the knowledge areas such as Big Data Analytics (BDA), Customer Relationship Management (CRM), marketing strategies, cross-selling and upselling. These knowledge areas will be crucial to understand in order to acquire the necessary skills that will be needed in the succeeding phases of the study.

The second phase will build on the theoretical aspects of phase one. A simulation model must be designed and developed in this stage. The *simulator* must be capable of generating pseudo-customer data containing personal information and purchasing behaviour at different retail stores. This stage includes theoretical aspects within the design of the system as well as

technical development of the system. The simulator will be verified by first creating smaller datasets with only a few customers and evaluating their purchasing patterns. The researcher will also introduce variation by including different distributions in the data. This stage and the next will be the most time-consuming phases in the study. Objective 1 will be achieved within the second phase of the study.

The design and development of the demonstrator is done in the third phase. The demonstrator must be able to analyse customer data to create customer profiles using the simulated data. Employing the created customer profiles, the demonstrator must also be able to identify personalised discount offers to individuals. This can all be done by using data analytics in the design and development of the demonstrator. At least two different data analytic techniques must be used in the demonstrator in order to evaluate the models.

Since this is a very novel approach and there are no comprehensive datasets available the researcher will place the focus on the comparison and evaluation of the analytical methods rather than the validation thereof.

The industry partner do not have access to real data including purchasing behaviour of customers at different outlets and for this reason simulated data is the only option. The following step will be for the industry partner to evaluate the proposed system by using real data.

An evaluation data set will be used during the design of the demonstrator to evaluate and compare the different analysis approaches. This data set will be simulated before the evaluation commences and the results must verify that the simulated data output are as expected.

Thereafter, PDOs will be introduced in the system and the demonstrator will incorporate the continued simulation of pseudo-customer data showing purchasing behaviour which is achieved within phase two. The PDO demonstrator will be evaluated whether it can correctly predict and propose PDOs even with the interference of promotional efforts in normal purchasing behaviour.

The fourth and final phase will include a discussion of the results composed by the demonstrator, incorporating the various data analytic techniques explaining the outcome of the study. This phase will also discuss the business value of this innovation along with a business case. Executing this phase will achieve Objective 2. The conclusion of the study must be in line with the research assignment.

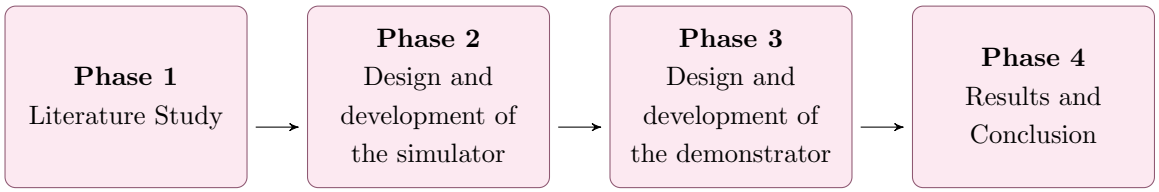


Figure 1.2: Summary of phases in research methodology

1.6 Deliverables envisaged

The deliverable envisaged is a demonstrator model developed as a software suite. This demonstrator will be able to access big data sets and create customer profiles by analysing the data using data analytics. Personalised discount offers are identified and offered to customers by using the customer profiles created.

1.7 Structure of this study

This chapter is followed by a literature study in Chapter 2. The literature study comprises of all the necessary theory that is needed to achieve the objectives. In Chapter 3 the system architecture of the proposed system is discussed. The proposed system is realised by a demonstrator and this chapter provides a holistic view of the proposed system. Chapter 4 contains the design and development of the simulator model of the proposed system. The simulator generates pseudo-customer data showing purchasing behaviour. Chapter 5 provides information regarding the design and development of the demonstrator. The demonstrator analyses the generated data to identify and propose personalised discount offers to customers. A discussion of the results of the system is presented in Chapter 6. Chapter 7 concludes this study with a business case, summary and appraisal of the work, and future work.

1.8 Chapter 1 summary

This chapter describes the background of where the study originated from. The objectives and scope display what will be achieved with this study and the research methodology shows how it will be achieved. This chapter also contains the deliverables that were envisaged by this study. Chapter 2 follows, with the literature study. In this chapter themes like data analytics, customer profiles, big data and system architecture are researched.

Chapter 2

Literature study

The previous chapter presented the motivation for this study and specified how the study will be executed to achieve the set objectives. This chapter consists of the following:

2.1 Customer Relationship Management

2.2 Marketing strategies and approaches

2.3 Pricing and special offers

2.4 Cross-selling and upselling

2.5 Customer profiling and customer segmentation

2.6 Knowledge discovery analysis

2.7 Big Data

2.8 Big Data Analytics

2.9 Data security and privacy

2.10 Systems architecture

2.1 Customer relationship management

The customer is the main variable in most enterprises and thus the management of the customer is crucial to ensure a successful future for the company. In the context of this study, the customer and their specific needs are addressed by the proposed model. For this, Customer Relationship Management (CRM) needs to be understood in order to create a system which fulfils the needs of the customers. The importance of CRM within an enterprise is explained in this section. This is accomplished by emphasising how to improve customer relationships using core activities and different CRM approaches.

2.1.1 Overview of CRM

CRM is the area within a business that allows the company to engage in customer interaction. CRM provides strategies, tools, processes and guidelines to build profitable relationships with customers. This lends support to the business strategy of a company and ensures success in a competitive marketplace (Mumuni and O'Reilly, 2014; Ngai et al., 2009; Soltani and Navimipour, 2016). According to Tsiptsis and Chorianopoulos (2009), CRM has two main objectives, which are:

1. Customer retention through customer satisfaction.
2. Customer development through customer insight.

Reinartz et al. (2004) identified three levels at which CRM can be practised, namely: functional, customer-facing, and company-wide. One of the objectives of the customer-facing perspective is to create a single view of a customer across all channels. Relationship initiation, maintenance and termination are the three dimensions or stages incorporated in the customer-facing level to ensure CRM process implementation. Reinartz et al. (2004) conceptualised a framework for the processes of CRM and evaluated the impact of the processes on economic performance. This was subdivided into two performance measure types: perceptual and objective. The activities identified by Reinartz et al. (2004) were acquisition management, recovery management, cross-sell and upsell management, referral management and exit management. These activities were accompanied by a customer evaluation at each stage which led to nine subdimensions.

Mumuni and O'Reilly (2014) furthered this research by investigating the impact on business performance having four dimensions: market share, revenue growth, profitability and overall improvement. In contrast with the research of Reinartz et al. (2004), Mumuni and O'Reilly (2014) evaluated the impact of the CRM processes on the individual dimensions as well as the combined dimensions. The core activities within the three dimensions identified by Reinartz et al. (2004) were adapted by Mumuni and O'Reilly (2014) and they are the focus of Subsection 2.1.2.

Customer Experience Management (CEM) is not a domain within CRM, but rather built upon CRM principles. A holistic definition of customer experience is defined by Gentile et al. (2007) as: "The customer experience originates form a set of interactions between a customer and a product, a company, or part of its organisation, which provoke a reaction. This experience is strictly personal and implies the customer's involvement at different levels". Du Plessis and De Vries (2016) present an overview of important works in literature on customer experience and it is evident that CEM has recently become increasingly important. Customer experience is important as it is becoming the distinguishing factor between competitors.

Table 2.1: CRM core activities (Mumuni and O'Reilly, 2014).

Portfolio Broadening Activities	Portfolio Rationalising Activities
Customer Acquisition	Retention Management
Customer Regain	Cross-selling and Upselling
Customer Referral Management	Exit Management

2.1.2 CRM activities

The CRM activities as seen in Table 2.1 are divided into two categories based on their main objective. The first part is the portfolio broadening activities. The function of these activities is to increase the existing customer portfolio of the company. The second section of the activities is focused on making the customer portfolio more effective and is named the customer rationalising activities.

Customer Acquisition refers to the identification of customers that would be most profitable. This also refers to those customers lost due to competition. This process includes activities such as customer segmentation of unknown data (Ngai et al., 2009). Some literature refers to this activity as customer identification or the relationship initiation dimension as described by Reinartz et al. (2004). According to the research of Thomas (2001), customer acquisition has a link to the activity of customer retention and is thus an important part in the overall CRM methodology. Customer acquisition is the time period from a customer's first purchase to the first repeat purchase.

Customer Regain refers to the activities involved in the regain of previous valued customers (Mumuni and O'Reilly, 2014). This is also part of the relationship initiation stage. Regain activities are very costly, as this has a negative effect on profitability. This activity is not as essential as that of customer retention.

Customer Referral Management is the activity of providing incentives to current customers for referring the enterprise to potential customers. This is used alongside marketing strategies discussed in Section 2.2 and is considered as part of the relationship maintenance dimension. Schmitt et al. (2011) did a study and found that referred customers have higher retention rates, higher contribution margins and are more valuable to the company over short- and long-time periods. Referral programmes are used to acquire new customers and have three unique characteristics. Firstly, they are deliberate and actively monitored. Secondly, they are based on the idea of using existing customers to reach potential customers. Thirdly, the existing customer is rewarded for bringing new customers (Schmitt et al., 2011).

Retention Management is the management of existing customers. Thomas (2001) defined the customer retention process as the beginning of a repeat purchase until the termination

of the relationship. Data from existing customers are analysed in order to find ways to retain these customers and this forms part of the relationship maintenance stage described by Reinartz et al. (2004). The problem emerges when this information is used to develop strategies for customer acquisition as well. Thomas (2001) argues that customer retention and customer acquisition are dependent processes and CRM decisions must take this biased factor into account. In the research of Salazar et al. (2015), one can find other benefits associated with retaining customers.

Cross-selling and Upselling are methods used to retain customers (Krishna and Ravi, 2016). From the empirical analysis done by Mumuni and O'Reilly (2014), cross-selling and upselling were the only portfolio rationalising activities which had a significant influence on the individual performance dimensions. The empirical analysis showed that organisations with higher CRM-compatibility have a stronger impact from the cross-selling and upselling activities on the combined performance dimensions. In the context of this study, cross-selling and upselling are fundamental principles within the proposed model. Cross-selling and upselling are discussed at greater length in Section 2.4.

Exit Management contains the activities related to helping unprofitable customers exit the customer portfolio. This forms part of the termination dimension identified by Reinartz et al. (2004). These typically focus on customers who are of low-value to the enterprise or problematic customers. Thus, it is more profitable for the company to use their resources on higher-valued customers.

2.1.3 CRM analysis

Customers are an enterprise's main source of revenue and thus the management of these customers must be a top priority for the enterprise (Tsiptsis and Chorianopoulos, 2009). CRM information can be used to gain knowledge about the customer and provide insights into the needs of the customer. CRM consists of three components which are operational CRM, analytical CRM and collaborative CRM. Dyché and Wesley (2002) describe analytical CRM to be the only way in which a company can maintain a progressive relationship with its customers. Operational CRM is used to execute sales and services based on the knowledge gained from the analytical CRM component (Krishna and Ravi, 2016).

Tsiptsis and Chorianopoulos (2009) highlight this as the point where analytical CRM can be beneficial to address the two objectives of CRM mentioned earlier – customer retention and customer development. *Data mining* and *machine learning* are used for these analytical purposes and these techniques are further explained in Section 2.8. Collaborative CRM is executed when technology is implemented to satisfy the needs of customers in real time (Krishna and Ravi, 2016). This study focus mainly on analytical CRM from this point onwards.

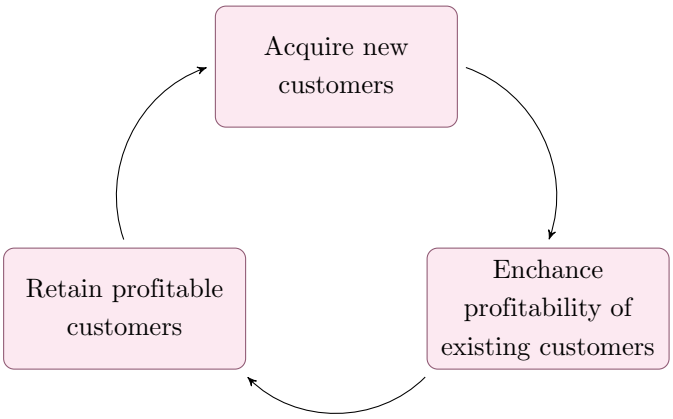


Figure 2.1: Customer life cycle (Krishna and Ravi, 2016).

The customer life cycle is divided into three phases as seen in Figure 2.1. Acquiring a new customer has already been discussed as being the first CRM core activity. As mentioned, segmentation can be used for this phase of the customer life cycle. Another approach to be used is direct marketing which is one of the focus topics in Subsection 2.2.2. The phase of enhancing the profitability of existing customers can be accomplished by investigating the *Customer Lifetime Value* (CLV) and conducting a *Market Basket Analysis* (MBA). These concepts are discussed in Section 2.6. In certain domains fraud detection, default detection and credit card scoring can also be used (Krishna and Ravi, 2016). The last phase, retaining profitable customers, is achieved by preforming customer churn detection and sentiment analysis.

CRM is not only achieved by activities such as marketing and sales but spreads beyond that to developing and maintaining relationships with customers. Salazar et al. (2007) defines CRM as not only a management philosophy that seeks to create, develop and enhance beneficial relationships with customers, but to maximise organisational profit and performance.

CRM and marketing are used concurrently within literature as well as in practice. CRM is focused on the relationship with the customer, while marketing assists with building profitable relationships with customers. With that said, the following section sheds some light on how marketing approaches can be used to achieve some core CRM activities discussed in this section.

2.2 Marketing strategies and approaches

A lot of different marketing strategies and approaches exist in literature and within the industry. The appropriate strategy and approach are defined by the industry the enterprise is in and the business strategy the enterprise has chosen. In this section an overview of marketing in general is given followed by different methods of communication with customers. This

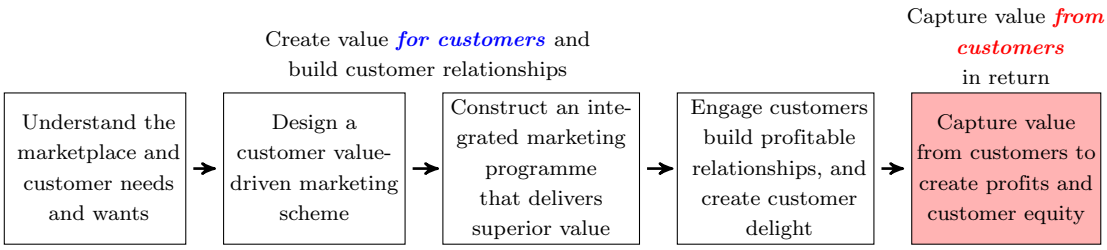


Figure 2.2: Marketing process (Kotler et al., 2018).

knowledge is required to find the ultimate means for marketing products and communicating with customers.

2.2.1 Overview of marketing

Marketing has numerous definitions, from broadly defined to a very specific business context. According to Kotler et al. (2018), marketing is the process by which companies engage with customers, build strong customer relationships, and create customer value in order to capture value from customers in return. The marketing process for creating and capturing customer value is summarised in Figure 2.2 and is discussed in great detail by Kotler et al. (2018).

The first four steps shown are focused on creating value for the customer and from this a customer-driven marketing strategy is designed. This is done by answering two questions: (1) deciding which customers the company will serve and (2) deciding how they will best serve their targeted customers. After choosing on an appropriate marketing strategy, an appropriate mix marketing framework is used (Kotler et al., 2018). This is done by using a marketing plan that consists of a blend of the marketing mix elements. The marketing mix framework is a set of tools used to transform and implement the marketing strategy of the company.

The term *marketing mix* was first conceptualised by Neil Borden in 1964. Borden (1964) proposed the approach of mix marketing in order to translate marketing strategies and plans into action. There were 12 mix marketing elements mentioned. In 1969 these 12 mix marketing elements where shortened by E. Jerome McCarthy into four elements, also known as the 4Ps: product, price, place, promotion (Kubiak and Weichbroth, 2010).

Goi (2009) conducted a study to identify the criticism in literature on the 4P framework and the propositions different researchers had for the mix model framework. A wide variety of different propositions arose. Some authors proposed more Ps, such as people, participants and process. From the work of Goi (2009) it was concluded that most of the literature still used the 4Ps as a defining view of a marketing mix framework. For the purpose of this study it is advised to adopt the 5P model with people as the added P. This decision was based on

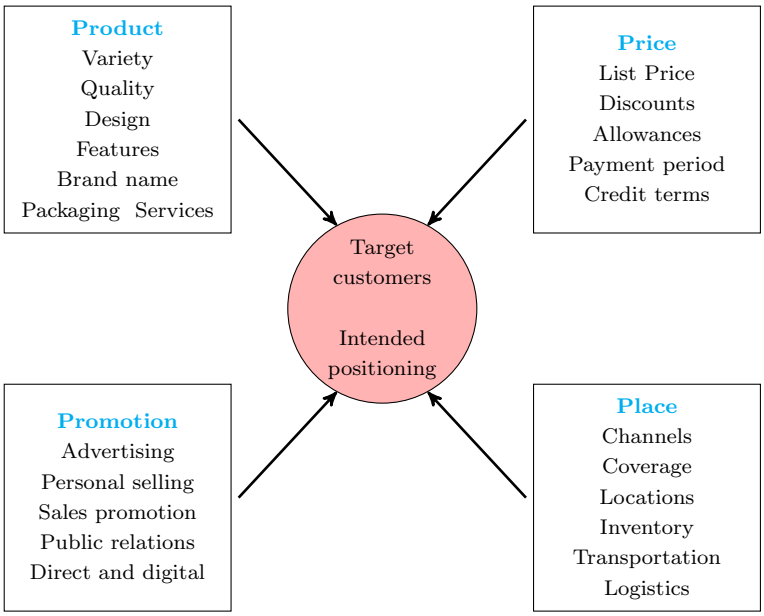


Figure 2.3: The 4Ps of the marketing mix (Kotler et al., 2018).

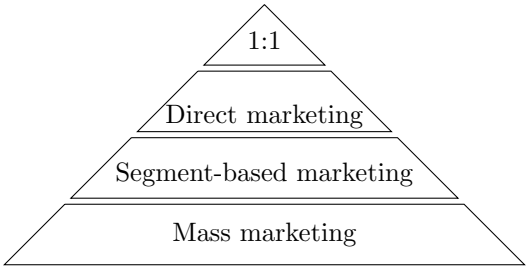


Figure 2.4: Marketing communications (Bounsaythip and Rinta-Runsala, 2001).

the importance of the customer as highlighted by Section 2.1. Figure 2.3 visualises the 4Ps of the marketing mix and their associated marketing tools.

In order to understand the marketing process, it is important to understand the different means in which a marketing strategy can be communicated to customers. There are different strategies to communicate marketing campaigns to different customers. This also answers the first question of a customer-driven marketing strategy stated earlier: deciding which customers the company will serve. Figure 2.4 visually explains the expense to revenue return ratio that is yielded from different communication approaches. The approaches are explained in more detail in Subsection 2.2.2.

It is clear to see that one-to-one marketing is much more effective based on the return ratio (Wedel and Kamakura, 2002). This type of marketing campaign sets the focus on each individual customer and their specific need and is much more effective than mass marketing.

Thomas et al. (2007) explained that these are not only marketing tactics, but marketing strategies. Strategies are the plans or methods whereas a tactic is the device used for accom-

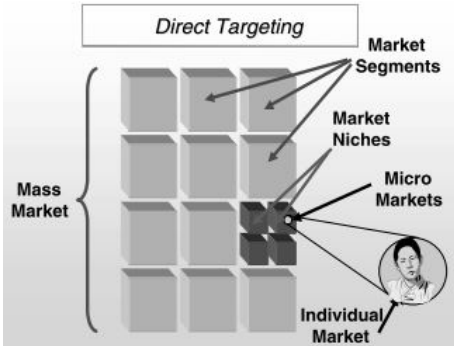


Figure 2.5: Direct marketing vs mass marketing (Thomas et al., 2007).

plishment at the end. The two main strategies are mass marketing and direct marketing.

Figure 2.5 explains the conceptual difference between mass and direct marketing. The strategies following in the next section are specialised direct marketing attempts and can be seen as strategies in their own right.

2.2.2 Different marketing strategies and approaches

Different types of communication approaches are used to interact with customers and the marketing campaigns are designed to focus on the respective groups of customers based on their needs.

Mass marketing is a traditional marketing practice used when launching a marketing campaign to an undifferentiated group of customers. In this scenario the focus of the campaign is to advertise the product or service and not the potential customer. All customers are treated with the assumption that they have the same needs and desires. Normally products that are launched using this campaign are products that are available in large quantities in almost every outlet (Dyché and Wesley, 2002). Comparing the revenue collected as a result of the campaign and the expenses thereof, mass marketing is not a cost-efficient approach as seen in Figure 2.4.

In the 1960s, *direct marketing* was introduced as a new approach to the traditional mass marketing. Direct marketing is based on the principle of communicating with a targeted group of customers through promotional mailing, media and other direct channels (Dyché and Wesley, 2002; Thomas et al., 2007). This is done by creating customer segments and altering marketing campaigns to address the needs of the customers better. Thus, employing direct efforts and resources to attract new customers that would be most tempted to the offer (Ngai et al., 2009). Dyché and Wesley (2002) stated that direct marketers were the pioneers of bettering marketing by monitoring the response to the advertisements more closely. According to Tsiptsis and Chorianopoulos (2009), direct marketing includes various campaigns. Some of

Table 2.2: Direct marketing campaign types (Tsiptsis and Chorianopoulos, 2009).

Campaign	**Goal**
Acquisition	Draw potential valuable customers away from competition.
Cross-selling and Upselling	Sell additional products, more of the same product or other products that are more profitable.
Retention	Preventing termination of relationships with valuable customers.

these campaigns are summarised in Table 2.2 and focus on achieving some core CRM activities as explained in Subsection 2.1.2.

According to Thomas et al. (2007), there are 12 steps to create a direct marketing process. The process outline is given below and can be further investigated in the book by Thomas et al. (2007). The 12 steps to create a direct marketing process are:

1. Customer Analysis – "the right behaviour"
2. Environmental Analysis – "the right context"
3. Competitive Analysis – "the right benefits"
4. Data mining & Profiling – "the right information"
5. Targeting – "the right market"
6. Positioning & Differentiating – "the right strategy"
7. Unique Selling Proposition – "the right offer"
8. Creative Marketing Communications – "the right message"
9. Direct Marketing Channels – "the right media"
10. Fulfilment & Service – "the right satisfaction"
11. Measurement & Assessment – "the right performance"
12. Adaptation and Innovation – "the right change".

In order to better direct marketing, another strategy must align with a direct marketing campaign. This strategy is referred to as *relationship marketing*. This type of marketing has a customer-centric focus to ensure long-term customer relationships. This is also the primary strategy that was used by Mumuni and O'Reilly (2014) to define the six core CRM activities

mentioned in Table 2.1. Paley (2007) defines relationship marketing as "the practice of building long-term satisfying relations with key parties – customers, suppliers and distributors – in order to retain long-term preference and business."

Traditionally, relationship marketing would refer to the interaction between suppliers and consumers. In the article by Paas et al. (2005), the authors acknowledge another long-term relationship that cannot be avoided any longer: the relationship between customers and products. Lately, there is a growing interest in customer retention and with that marketing attention shifted from being mutually independent activities to being loyalty-based cross-selling and upselling opportunities.

The relationship with a customer is based on three dimensions according to Paas et al. (2005): the length of time, the balance of interest, and the direction and intensity of communication. In the past, transactions were seen as discrete events not containing any significant value. More recently, the long-term relationship between a customer and supplier is expressed via transactions. This is seen when investigating the popularity of customer loyalty programmes and CRM programmes within the CRM domain.

Paas et al. (2005) identified four customer-product interactions. The most known concept is that of customer needs. When the needs of a customer are identified, appropriate product recommendations can be made. Alongside the customer needs, is the life cycle hypothesis. Throughout the life cycle of the product or the customer the needs change and this shows that acquisitions do not occur randomly. Another interaction is the one related to revealed preferences. The problem with this concept is that customer-product interactions are based on actual acquisitions, where the argument rises that customers do not acquire a product they do not need. Thus, this relates to revealing customer needs and does not explain customer-product interactions.

The last concept is brand loyalty. Unlike the other concepts mentioned in this section, brand loyalty is of significant value for the analysis of product-customer interaction. Brand loyalty expresses the customer's consistent preference for a particular brand by purchasing the offer repeatedly.

Personalised marketing campaigns are used by companies to target specific customers (Kamber et al., 2012; Khodakarami and Chan, 2013). Thomas et al. (2007) explain that direct marketing goes beyond the market segmentations and focuses on micro-markets as well as on individual customers. This aspect of direct marketing is known as *one-on-one marketing* or *targeted marketing*. The idea of customising the offer presented to a customer based on an individuals' needs and the personalisation of the customer are the key concepts of one-to-one marketing. When pairing this marketing strategy with the technological innovations of today,

it is possible to customise the marketing message individuals receive and the means whereby they receive it.

Dyché and Wesley (2002) and Changchien et al. (2004) identify two main approaches of personalisation. First is *rule-based personalisation* or *content-based*, where established rules dictate the personalisation. This approach measures the degree of similarity between items which customers purchased in the past (Bose and Chen, 2009; Changchien et al., 2004). For example if someone buys a book online, the recommender system would recommend the next book of the series to the buyer before the checkout point. Rule-based personalisation is normally hard-coded into the software and is therefore difficult to maintain.

The second type is that of *adaptive personalisation*, also known as *collaborative filtering*. This type of personalisation learns as time passes: adaptive personalisation uses the behaviour of similar customers or tries to find similarities between customers' preferences. Thus, for example, a customer buys a film of a certain genre, the system will recommend another film of the same genre. Both these types of filtering are used for recommender systems in the e-commerce industry (Dean, 2014; Erl et al., 2015; Kamber et al., 2012).

Wedel and Kamakura (2002) state that even with one-to-one marketing, customer segmentation is not precluded. Enterprises develop a limited number of marketing strategies which are based on the different available segments. Some companies have developed one-to-one marketing strategies to increase their profits, but the usage thereof as an implementation tactic does not prevent market segmentation as a general approach.

Customer data are used to identify the needs of an individual for the purpose of direct marketing. These concepts are referred to as customer segmentation and profiling and are further discussed in Section 2.5.

According to Chen et al. (2005a) and Jiao et al. (2006), one-to-one marketing campaigns are supported by analysing and predicting customer behaviour to personalise marketing campaigns. One-to-one marketing is used alongside relationship marketing to enhance customer retention. The idea of targeted marketing is one of the core principles of this study when looking at different marketing strategies. This study focuses on personalising offers for individuals and with that a one-to-one marketing strategy is used.

The following section will focus on pricing and special offer strategies which are seen as part of the marketing mix framework. For the purpose of this study, this is discussed in a section on its own in order to emphasise its importance.

2.3 Pricing and special offers

Pricing strategies and tactics are covered widely in literature. Depending on the product or service, the business strategy and marketing strategy, different pricing tactics can be used. Price is also one of the 5Ps mentioned in the framework of the marketing mix and is thus a vital element to discuss.

For the purpose of this study, this section will place the focus on pricing for promotional reasons which relate to the promotions and pricing strategies that are referred to in Section 2.2.

Pricing guidelines were established in the book by Paley (2007) in order to increase the chances of success. The guidelines are as follows:

1. Establish the pricing objectives.
2. Develop a demand schedule for the product.
3. Examine competitors' pricing.
4. Select the pricing method.

Changchien et al. (2004); Paley (2005); and Kotler et al. (2018) provide literature regarding pricing strategies in great detail. Some of the pricing strategies are summarised in Table 2.3.

Table 2.3: Pricing strategies, from Changchien et al. (2004); Paley (2005) & Kotler et al. (2018).

Purpose	**Strategy**	**Description**
General pricing	Customer value-based	Setting the prices based on how much the customer will pay and the price must meet the expectations of the customers. There are two methods namely, perceived-valued pricing and demand-backward pricing.
	Cost-based	Setting prices based on cost of production, distribution, *etc.* and adding a profit margin to the cost of the product. The five methods available are mark-up, key-stoning, profit maximisation, break-even and target-return.
	Competition-based	Setting prices based on competitors' strategies, costs, prices and offering. The two main methods are going-rating, sealed-bid.
New Products	Skimming	Products are introduced at a high price and the price lowers throughout the life cycle of the product.
	Penetration	Products are introduced at a low price with the idea of penetrating the market and ensuring a greater market share faster.
Existing Products	Product-mix	Product-line: Setting prices across an entire product line.
		Captive-product: Selling a basic product at a reduced price, but selling an essential consumable (which complements the basic product) at a higher price margin.
		Product-bundle: Marketing two or more goods in a single package for a special price.
		By-product: Setting a price for by-products to help offset the costs of disposing of them. Optional-product: Pricing optional or accessory products along with the main product.
	Psychological	Setting prices to products which have a psychological influence on the customer. Prices are perceived lower than they actually are.

Continued on next page

Table 2.3 continued

Purpose	Strategy	Description
	Segment	Adjusting prices based on different customers, products and locations.
	Geographical	Adjusting prices to account for the geographical location of the customers.
	Flexible/Differential	Selling the same product in different markets at different times at diferent prices. Also used to meet competitive market conditions.
	Promotional	Temporary reducing of prices to spur short-run sales.
	Discount and Allowance	Reducing prices to encourage customer response such as volume purchase, pay early or promoting a product.
	Loss-Leader	Pricing a product low in order to create cross-selling opportunities.
	Life cycle pricing	The pricing strategy is altered to match the requirements of the different stages of the product life cycle.

From Table 2.3, a promotional pricing strategy is the most relevant in this study. The discount and allowance and the loss-leader pricing strategies can also be incorporated in this study along with the promotional pricing strategy.

Promotions is also one of the 5Ps in the marketing mix framework. *Promotional pricing* is when products are temporarily sold at a lower price than the listed price (Kotler et al., 2018). Sales promotions are all the promotional efforts that cannot be classified as advertising, personal selling or publicity. Paley (2005) defines the difference between sales promotion and advertising as: sales promotion is an incentive to buy and advertising offers a reason to buy. The customer is encouraged to buy a product because of added value or providing special incentive. Also, sales promotions are part of the overall marketing strategy and involve a variety of company functions in order to work efficiently.

Two types of promotional strategies exist, according to Campbell and Diamond (1990). The author also states that most customers have a reference price of what the product they are looking for might cost. The two categories of promotions are (1) non-monetary promotions and (2) monetary promotions. *Non-monetary promotions* refer to promotions which have an added product or service. *Monetary promotions* are usually discounts and rebates. Customers perceive these types of promotions differently. Normally, non-monetary promotions can be seen as a gain and are considered separately from the reference price a customer might have, whereas monetary promotions can be viewed as a potential loss and can sometimes affect the reference price of the customer. It is for this reason that determining an appropriate promotional strategy and price is essential.

Promotions provide an area for creativity and flexibility, and can be implemented by using one of the following applications (Paley, 2007):

1. **Consumer promotions:** Samples, coupons, cash refunds, premiums, free trials, warranties, and demonstrations.

2. **Trade promotions:** Buying allowances, free goods, cooperate advertising, display allowance, push money, video conferencing and dealer sales contests.

3. **Sales force promotions:** Bonuses, contests, and sales rallies.

Discounts are simply when a retailer sells products at a lower price in order to increase sales and reduce inventories. *Special event offers* are used in certain seasons to draw more customers. *Limited-time offers* or *flash sales* are used to create buying urgency. This form of promotion also makes the customer feel special to have received the offer. The researcher sees this type of promotion as the cornerstone of this study.

Promotional pricing, unfortunately, does not only have positive effects. During high-seasonal times, industries can experience a promotion bomb, where all marketers ambush customers with promotional sales. In this time marketers can cause buyers wear-out and create pricing confusion. Also, constant promotional pricing lowers the brand-value a customer has regarding the product. Frequent price promotions also create scenarios where customers would rather wait until a product is on sale. One of the events sales managers must be careful of is giving too many coupons or discount, which in return makes the customer lose the feeling of special treatment (Kotler et al., 2018).

It is for this reason that promotional pricing policies are needed within a business. Nagle et al. (2014) state that for consumer products promotional pricing strategies are of utmost importance, not only for ensuring the company still receives a part of the profit margin, but also to review the effectiveness of the promotion.

Changchien et al. (2004) developed a decision support system for online personalised sales promotions in electronic commerce. In the study, the author undertakes sales promotion strategies and pricing strategies in marketing strategies. Sales promotion strategies consist of three subdivided strategies which are general promotions, cross-selling and upselling strategies. Cross-selling and upselling are reviewed in more detail in Section 2.4. These strategies are seen everywhere in the retail industry and are not a novel event for customers. The challenge is to better the promotions by personalising them for each individual customer. The authors address this by applying personalised offers to online purchases. The challenge for this study will be to apply it to *Fast Moving Consumer Goods* (FMCG).

It is clear in this section that promotions are a key part of this study and will be referred to often. The next section explains the principles of cross-selling and upselling and their importance.

2.4 Cross-selling and upselling

Customer retention is considered as one of the core activities of CRM, as described in Subsection 2.1.2. Cross-selling and upselling are methods used to retain customers. Cross-selling and upselling are in themselves also considered to be core CRM activities. This leads to emphasising the importance of these principles and will be discussed within this section. This study aims at bettering targeted marketing based on individuals' specific needs and can be accomplished by proposing cross-selling and upselling opportunities to customers.

Cross-selling occurs when customers are offered the opportunity to purchase alternative products or services during their current buying process. These additional offers are related to or complement their original purchase. This refers to products that are considered in a

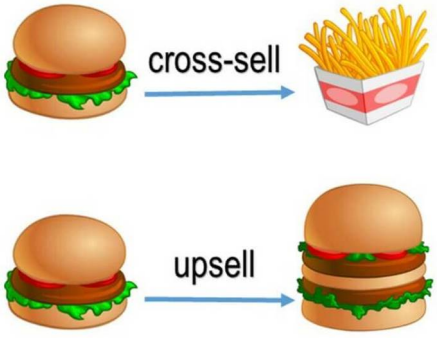


Figure 2.6: Cross-sell vs. upsell

different product category. An everyday example of this is when a customer is asked whether or not they would like fries with their burger.

Cross-selling is used to ensure the company captures a larger share of the consumer market by increasing the number or services the customer acquires from the company. It can also be seen as a strategy to ensure a competitive advantage amongst peers (David, 2005; Krishna and Ravi, 2016; Kubiak and Weichbroth, 2010; Salazar et al., 2007).

Up-selling is a technique described by Schiffman (2005) as "what happens when you take the initiative to ask someone who already has purchased something you offer to purchase more of it – or more of something else ". The focus is on motivating the customer to acquire a more expensive version than what was considered (David, 2005; Kubiak and Weichbroth, 2010). Thus, upgrading the products in the same product category (Krishna and Ravi, 2016). An example of this is when a customer is offered a more expensive product.

Up-selling can also include keeping customers consuming by upgrading the conditions of previous purchases (Salazar et al., 2007). A promotion, mentioned in Section 2.3 and seen in almost all retails stores, is also a method of upselling. Another method is making customers alert of alternative products by including information about them with the original acquisition. Flyers given along with the invoice are an example presented by Schiffman (2005).

Figure 2.6 visually explains the difference between cross-selling and upselling. Cross-selling and upselling are methods used to ensure time and money are saved when executing marketing strategies.

The three objectives required to identify cross-selling and upselling opportunities are identified by Salazar et al. (2007) as:

1. Understanding the acquisition pattern of the customer.
2. Identifying the factors which impact the repurchase decision of the customer.
3. Forecasting the time of possible repurchases.

The Market Basket Analysis (MBA), amongst others, is one of the well-known knowledge discovery methods used in practice to pursue these objectives (Krishna and Ravi, 2016; Kubiak and Weichbroth, 2010; Tsiptsis and Chorianopoulos, 2009). The different analysis approaches are discussed in Section 2.6.

The analysis of customer data with knowledge discovery analysis and data mining methods, described in Section 2.6 and Subsection 2.8.3 respectively, is an effective manner to identify cross-selling and upselling opportunities (Kubiak and Weichbroth, 2010; Salazar et al., 2007). Effective cross-selling and upselling can only happen when retailers fully understand customers in terms of their needs. This is where analytical CRM is the main focus to create customer segments and customer profiles and build a better relationship with the customers.

Customer segmentation and profiling are discussed by the researcher in the upcoming section. For the purpose of this study, it is important to understand that using customer profiles and data mining leads to cross-sell and upsell opportunities which can be presented to the customer with their personalised offer and by doing this the company creates customer value and customer retention.

2.5 Customer profiling and customer segmentation

This section presents an overview of customer profiling and customer segmentation, the difference between the two and how it is used in this study. Approaches to develop customer profiles are investigated and explained.

2.5.1 Overview of customer profiling and customer segmentation

The terms customer profiles and profiling have been seen in recent literature reviews. Customer profiling and customer segmentation are often used interchangeably.

Customer profiling attempts to create a model of the customer used to decide on appropriate strategies and tactics to meet the demand of the customer by creating a customer profile (Shaw et al., 2001). Customer profiles describe customers based on their attributes (Bounsaythip and Rinta-Runsala, 2001). According to Adomavicius and Tuzhilin (2001), a comprehensive customer profile consists of two sub-profiles: factual and behavioural. The *factual profile* tells who the customer is and *behavioural profile* describes what the customer does.

Customer profiling is a tool used to personalise individuals in order to understand and provide to their unknown needs. This improves customer service for better customer satisfaction and customer retention, which is one of the core CRM activities listed in Subsection 2.1.2. Marketers use these profiles for targeted marketing in which they present an offer to

Figure 2.7: Customer segmentation vs. customer profiling

a customer at a time the customer would be most susceptible to that offer (Lanjewar and Yadav, 2013; Romdhane et al., 2010).

Customer profiles can predict the behaviour of the customer discovering similar patterns from the collected behavioural data. An example of behavioural data in the context of this study is transactional data at one of many participating retail outlets. An estimation of usage behaviour, in this case products purchased, can be obtained by using each customer profile. Profiling thus attempts to discover knowledge within the data of the customer that was not already known (Bounsaythip and Rinta-Runsala, 2001; King and Jessen, 2010; Lanjewar and Yadav, 2013). It is for this reason that researchers refer to understanding the *unknown needs* of a customer. The right-hand side of Figure 2.7 visually explains the principle of customer profiling. This can include information such as age, gender, geographic information, economic conditions, *etc.* The left-hand side illustrates customer segmentation which is the following topic of discussion.

Customer Segmentation is referred to when customers are divided into homogeneous groups based on shared characteristics or habits (Krishna and Ravi, 2016; Wedel and Kamakura, 2002). A segment describes a certain behaviour of a group of customers as well as shared properties. This is done in order to develop differentiating marketing strategies based on their characteristics (Tsiptsis and Chorianopoulos, 2009). Similar to customer profiles, customer segmentation can be used to identify certain unknown needs of a group of customers (segment).

In the light of the amount of data that must be analysed these days, Fan et al. (2015) argue that customer segmentation is becoming more challenging based on similar traits of customers. To identify the specific need of each individual and market the appropriate product to them, each customer must be profiled individually.

Bounsaythip and Rinta-Runsala (2001) state that customer profiling is performed after customer segmentation. The researcher does not agree that customer profiling must necessarily occur after segmentation. The objective of the project determines whether segmentation or profiling must be used. The choice between profiling or segmentation of data depends

on the knowledge the user wants to obtain. Tsiptsis and Chorianopoulos (2009) verify this by explaining that profiling of segments can be used in order to take full advantage of the segmentation in subsequent marketing activities. Prospective customers can also be identified by using external data sources (Bounsaythip and Rinta-Runsala, 2001).

The researcher finds it understandable that customer segmentation and customer profiling are often misunderstood as the same concept. In the context of this study, the two terms will be used as they were defined in this section. The specific needs of each individual customer must be identified by using their historical buying behaviour and with that in mind customer profiling is the appropriate manner to do so. Customer segmentation can be used to allocate a new customer to a segment based on the sign-up information provided by the customer. The subsequent section discusses the development of customer profiles.

2.5.2 Approaches to develop customer profiles

As described in Section 2.1, customer profiling and segmentation can be used to better CRM (Tsiptsis and Chorianopoulos, 2009). Profiling is done by collecting information of a customer and building a customer's behaviour model (Adomavicius and Tuzhilin, 2001; Bounsaythip and Rinta-Runsala, 2001; Romdhane et al., 2010).

According to the research of Jansen (2007), segmentation can commence without knowledge of the data or defining the segments in advance. This does not apply in the process of developing customer profiles. A complete set of individual customer data must be available before profiling can commence. The availability of data and choice of development technique dictates which features are used for profiling. The factual profile mentioned in Subsection 2.5.1 is derived from demographical data of the customer, but can also contain information derived from transactional data such as preferences. The behavioural profile can be derived from transactional data which are records of a customer's purchases during a specific period of time (Adomavicius and Tuzhilin, 2001; Bounsaythip and Rinta-Runsala, 2001). This is the type of behavioural data that will be used in this study. Another type of behavioural data are online web usage data and social media data.

A list of transactional characteristics helping with marketing decisions was provided in the research of Shaw et al. (2001). This list complies to most of the characteristics that would be needed for the system created during this study. The list consists of:

- frequency of purchases,
- size of purchases,
- recency of purchases,

- identifying typical customer groups,
- computing customer lifetime values,
- information regarding prospective customers,
- and success/failure of marketing programmes.

These characteristics can be used along with the general marketing knowledge gained from Section 2.2 to identify appropriate offers for specific customers.

Customer profiling is one of the cornerstones of this study and it is crucial to understand the reason for using it within the context of marketing and personalised offers. The upcoming sections stray from the broad spectrum concepts which were discussed up to this point. They will place the focus on the analytical aspects needed to analyse customer data. The association mining and sequential pattern mining are two of the approaches available to create customer profiles from their behavioural data. These topics are discussed in the next chapter.

2.6 Knowledge discovery analysis

The knowledge discovery within data are a crucial concept to understand before looking into the technical detail of data analytics. Chen and Zhang (2014) illustrated a generic knowledge discovery process which is shown in Figure 2.8. A variety of knowledge discovery processes will be discussed in Subsection 2.8.2.

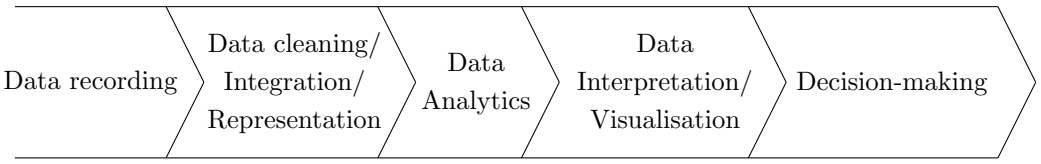


Figure 2.8: Knowledge discovery process, adapted from Chen and Zhang (2014).

This section will aim the focus on the concepts mentioned during the discussion of the customer life cycle in Section 2.1.

2.6.1 Customer Lifetime Value

The *Customer Lifetime Value* (CLV) is used to refer to the future expected revenue the company will obtain based on their relationship with the customer. This can be tangible or intangible benefits that cause the customer to be of value to the company (Krishna and Ravi, 2016). The method of *Recency, Frequency* and *Monetary* (RFM) value is commonly used to estimate the value of a customer.

Table 2.4: Advantages and disadvantages of RFM (Dursun and Caber, 2016).

Advantages	**Disadvantages**
Powerful tool to assess CLV	Insufficient to generate successful marketing campaigns based on the three indicators
Effective in predicting response	A high correlation exists between frequency and monetary values
Basis for a continuing stream of techniques to improve customer segmentation	Ignorance of potential and non-profit customers
	RFM indicators' importance differs in every industry

The RFM analysis is used to comprehend the purchasing behaviour of customers (Kahan, 1998). This makes RFM analysis also beneficial for the targeted marketing strategies mentioned in Section 2.2. According to Tsiptsis and Chorianopoulos (2009) and Chen et al. (2005a), RFM is commonly used in the retail industry to detect the change of customer behaviour and this is used to alter marketing strategies accordingly.

The 'Recency' indicator measures the recency of purchases or the time period since the most recent transaction. This is the time that has elapsed since the previous transaction the customer made. 'Frequency' is used to indicate how frequently the customer engages in transactions within a certain time period. It is also noted as the average number of purchases per unit of time. The last indicator is the 'Monetary' value which the customer spends on a purchase or the average value per purchase (Dean, 2014; Paas, 1998; Tsiptsis and Chorianopoulos, 2009).

Advantages and disadvantages of the RFM analysis were identified by Dursun and Caber (2016) and can be seen in Table 2.4.

For CLV, a 5-score analysis is used for all three of the RFM indicators. The basic approach is to divide and sort customers into equal classes for each indicator independently. After that each class is scored according to each RFM indicator. Taking the recency indicator as example, the customers are sorted and divided into five equal classes. The recency class with the lowest recency (the highest ordinal time period) are awarded a score of one and this will be the lowest 20% of the total customers. The recency class with the highest recency (most recently purchasing customers) are awarded a score of five. This is done for the other two indicators as well (Dean, 2014; Tsiptsis and Chorianopoulos, 2009). It is important to decide on the number of levels or scores the indicators will be ranked, for this leads to calculating the number of clusters necessary.

The number of clusters can be calculated by

$$\text{Number of Clusters} = \text{Level}_{Recency} \times \text{Level}_{Frequency} \times \text{Level}_{Monetary}.$$

Using the example of a 5-score analysis, the number of clusters is 125 ($5 \times 5 \times 5$). Thus, the level of each class for a respective indicator is the number of the scoring analysis representing the class. The CLV can be calculated as the product of the scores from the three RFM indicators. To make this clear, for a 2-score analysis (eight clusters), above or below average, the top RFM score would be eight and thus would this also be the CLV.

Previous work highlighted different scoring methods (Dursun and Caber, 2016). It was criticised that 'the customer quantile method' either grouped customers with different behaviour together and arbitrarily divided customers with similar behaviour. From this the 'customer behaviour quantile scoring' was proposed. This method scored customers based on each quantile having almost equal monetary values. A weighted approach was also identified which examines the relative importance of the RFM indicators via the Analytic Hierarchy Process (AHP) algorithm (Dursun and Caber, 2016). An evaluation of this approach would look like

$$\begin{aligned}\text{RFM score} = (\text{Level}_{Recency} \times \text{Weight}_{Recency}) + (\text{Level}_{Frequency} \times \text{Weight}_{Frequency}) + \\ (\text{Level}_{Monetary} \times \text{Weight}_{Monetary}).\end{aligned}$$

Another method of using the RFM is using the original data instead of the coded data. The mean for each RFM indicator is calculated and the RFM scores are indicated as above average using '↑', and below average using '↓'. This type of scoring analysis will have eight clusters.

k–means, a common clustering algorithm, is used to evaluate the optimal number of clusters depending on the customer data being analysed. More about clustering can be found in Section 2.8. Based on the optimal number of clusters, an appropriate scoring analysis can be chosen. For each RFM indicator, the clusters are scored and the product of these scores identifies the CLV.

Figure 2.9 shows the *growth matrix* of the Boston Consulting Group (BCG), which classifies customers into four segments based on their customer value. The four groups are the *best customer, frequent customer, spender customer,* and *uncertain customer* (Chen et al., 2005a).

RFM models can be used to evaluate the CLV scores of customer segments and place them within one of the four groups of the BCG growth matrix, or each individual cluster can represent a different type of customer and, thus, an alternative marketing strategy must be used. Applications of RFM models can be found in Dursun and Caber (2016), Chen et al. (2005a) and Dean (2014).

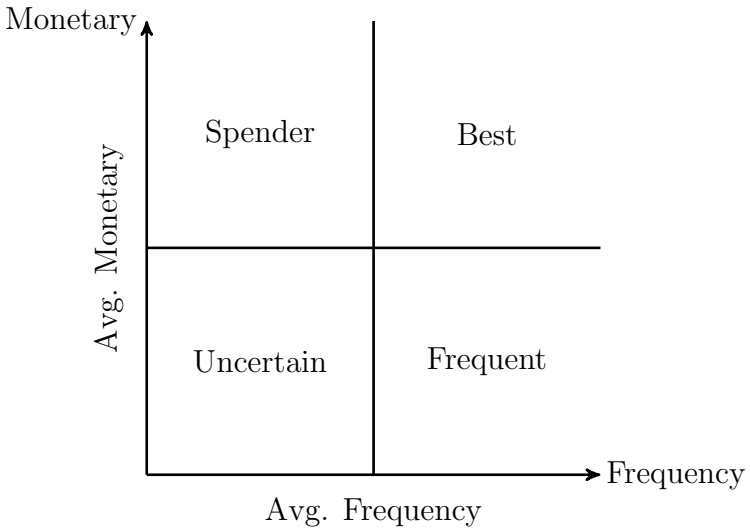


Figure 2.9: BCG customer value matrix (Chen et al., 2005a).

The researcher found that RFM is mostly used on customer segments, which is a group of customers with similar buying patterns. For the purpose of this study, an individual analysis is needed to determine certain purchasing behaviour. CLV and the RFM analysis can still be used for analysing different market segments before focusing on each individual customer. This leads in to the following section which looks into certain purchasing behaviour and the analysis that can be done to determine which products are acquired together.

2.6.2 Market Basket Analysis

Market Basket Analysis (MBA), also known as *association analysis*, is based on the concept that customers frequently purchase certain products together (Dyché and Wesley, 2002). It aims at maximising the transactional intensity and value of the customer (Ngai et al., 2009). This approach studies customers' buying behaviour by looking for item sets that are frequently purchased together (Bounsaythip and Rinta-Runsala, 2001; Kamber et al., 2012; Krishna and Ravi, 2016).

Association rule mining is used for MBA and can be used to identify cross-selling opportunities for customers and better marketing opportunities. Products with strong associations should not be promoted at the same time (Giudici and Passerone, 2002). Frequent item sets are discovered and used to generate association rules as explained by the examples of Kamber et al. (2012). Association rule discovery is used to discover rules which identify patterns of behaviour by analysing datasets. These rules are used within the MBA, but the terminology is sometimes used interchangeably.

Association rules consist of two measures, and are explained in Table 2.5. Take for example:

When someone buys shampoo she also buys conditioner 60% of the time

with a support of 2%. Shampoo is bought 5% of the time. Conditioner is bought 6% of the time.

Table 2.5: Association rule mining, from Bounsaythip and Rinta-Runsala (2001); Kamber et al. (2012); Tsiptsis and Chorianopoulos (2009).

Measure	Explanation	Example
Support	The support indicates the frequency of the association. How many times are items purchased together? To be of business value a minimum support value is needed.	Within all the transactions under analysis, shampoo and conditioner appear together 2% of the time.
Confidence	The confidence assesses the strength and predictive ability of the association. "How likely the successor given the predecessor?" or "How much is an item dependent on another?"	If shampoo is bought there is a 60% confidence that conditioner will also be bought.
Lift	Lift measures the difference between the confidence of a rule and the expected confidence. The measure of the strength of an effect. Lift is calculated as the ratio between two products' expected confidences.	The 5% and 6% are the expected confidences of the products, regardless of what else is purchased. If this example has a lift below one it suggests that it is less likely for people to buy these products at the same time.

Thus, **X** and **Y** appear together in only 2% of the transactions, but when **X** appears there is a 60% chance product **Y** will also appear. The 2% presence of **X** and **Y** together is the support measure of the association rule and 60% is the confidence of the association rule (Kamber et al., 2012).

Association models can be applied to selected levels of analysis. Transactional data summarises purchases at transactional level, thus items bought at a single visit to a store. Aggregated information is at customer level and assesses what is bought during a specific time period by each customer or the current product mix of a customer (Tsiptsis and Chorianopoulos, 2009).

A basket table is one of the available tabular formats which can be used for association modelling. These tables are also known for having a horizontal format, contain categorical or flag fields, which specify the presence or absence of a purchased product. The fields denoting the purchased product are the content fields. The analysis ID field can be the transaction ID or the customer ID, depending on the level of analysis. This type of format becomes

Table 2.6: Basket table example (Tsiptsis and Chorianopoulos, 2009).

Input-Output fields				
Analysis ID field	**Content fields**			
Transaction ID	**Product 1**	**Product 2**	**Product 3**	**Product 4**
101	True	False	True	False
102	True	False	False	False
103	True	False	True	True
104	True	False	False	True
105	True	False	False	True
106	False	True	True	False
107	True	False	True	True
108	False	False	True	True
109	True	False	True	True

inefficient when the number of products increases and in some cases product grouping is used (Bounsaythip and Rinta-Runsala, 2001). An example of a basket table from Tsiptsis and Chorianopoulos (2009) is shown in Table 2.6.

R. Agrawal and R. Srikant proposed a seminal algorithm, Apriori, in 1994 to be used in mining frequent item sets for Boolean association rules (Kamber et al., 2012). Other algorithms, identified by Kamber et al. (2012), are also available as the *Apriori algorithm* but with improved efficiency. Algorithms are divided into three categories: (1) Apriori-like alogrithms, (2) Frequent pattern growth-based algorithms, (3) algorithms that use vertical data format.

Some models, such as Apriori can analyse the dataset directly from the *transactional input data*, which is captured in a *vertical format* (Bounsaythip and Rinta-Runsala, 2001). This format is more normalised than the *horizontal format*. For the vertical format, two data fields are present: The *content field* – denoting the items and the *analysis ID field* – denoting the level of analysis. Multiple records are thus linked by having the same ID.

Tsiptsis and Chorianopoulos (2009) explains this using an example shown in Table 2.7. In this example, the transactional ID is used, thus the analysis is on transactional level. In the case where the analysis ID is chosen to be the customer ID, the data would be internally aggregated and analysed on customer level.

To show an example of association rules from this transactional data the first two rules are given in Table 2.8.

Chen et al. (2005b) conducted research on using MBA in a multiple store environment and proposed an Apriori-like algorithm. The authors found that this evaluation was more efficient and advantageous over traditional methods in the cases where stores are diverse according to

Table 2.7: Transactional dataset (Tsiptsis and Chorianopoulos, 2009).

Input-Output field	
Analysis ID field	**Content field**
Transaction ID	**Products**
101	Product 1
101	Product 3
102	Product 2
103	Product 1
103	Product 3
103	Product 4
104	Product 1
104	Product 4
105	Product 1
105	Product 4
106	Product 2
106	Product 3
107	Product 1
107	Product 3
107	Product 4
108	Product 3
108	Product 4
109	Product 1
109	Product 3
109	Product 4

Table 2.8: Association rules for transactional dataset (Tsiptsis and Chorianopoulos, 2009).

Rule ID	**Successor**	**Predecessor**	**Support %**	**Confidence %**	**Lift**
Rule 1	Product 4	Product 1 and 3	44.4	75.0	1.13
Rule 2	Product 4	Product 1	77.8	71.4	1.07

size, location and product mix. The article includes alterations in the algorithm to overcome problems such as seasonal sales and some stores not selling certain products. This article can be helpful in this study and will be referred to again.

Other related literature on association rule mining is Adomavicius and Tuzhilin (2001); Giudici and Passerone (2002); Au and Chan (2003); Chen et al. (2005a); Demiriz (2004); Jiao et al. (2006); Lee et al. (2006) and Wang et al. (2004).

For the focus of this study, association rule mining and thus MBA will be an appropriate approach to create customer profiles based on analysing the customers' transactional history. Association rule mining is also suitable for identifying cross-selling and upselling opportunities. When adding a time element to MBA it is often seen as Sequence Pattern Analysis (SPA) and this will be the next topic of discussion.

2.6.3 Sequential Pattern Analysis

Alongside association-rule mining, *Sequential Pattern Analysis* (SPA) exists when adding the factor of time with the association rule modelling. This creates the analysis of associations over time in order to discover patterns or series of events happening in a specific sequence. The generation of sequential association rules are analogous to those mentioned in MBA with the difference that if things happen in a certain sequence, the probability of a certain event to occur next is increased (Tsiptsis and Chorianopoulos, 2009).

As with association rule mining (which was first mentioned by Agrawal and Srikant in 1994), SPA was also investigated by these researchers in 1995 (Changchien et al., 2004; Mooney and Roddick, 2013). SPA is defined as *"Given a database of sequences, where each sequence consists of a list of transactions ordered by transaction time and each transaction is a set of items, sequential pattern mining is to discover all sequential patterns with a user-specified minimum support, where the support of a pattern is the number of data-sequences that contain the pattern"* (Mooney and Roddick, 2013).

In the research by Mooney and Roddick (2013), a variety of reformulations of this definition are provided. Since association mining started within transactional data, this was the same start for SPA. However, this type of analysis can be used in various domains and applications such as genome searching (biotechnology), alarm data in telecommunications networks (telecommunication) and population health data (health care).

SPA algorithms can also be categorised in the same categories as association rule mining. The categories as described by Mooney and Roddick (2013) are (1) *Apriori-like*, (2) *horizontal or vertical format*, or (3) *projection-based pattern growth algorithms*. The variety of domains in which SPA can be used led to algorithmic developments in each domain respectively. Frequent item sets, mentioned in Subsection 2.6.2, are used for normal association rule mining and sequential rule mining. The difference comes where Apriori-like algorithms for MBA discover

Table 2.9: Advantages of SPA (Bounsaythip and Rinta-Runsala, 2001).

Advantages	Explanation
Coupons and Discounting	Offer simultaneous discounts on products that are frequently bought together or after each other.
Product Placement	Place products with strong relationships close to each other in order to take advantage of the strong natural correlation between products.
Timing and Cross-marketing	Useful for marketing new products at the right time based on the sequential association rules.

intra-transaction associations and algorithms for SPA focus on inter-transaction associations (Mooney and Roddick, 2013).

SPA can be used for marketing purposes such as cross-selling and upselling. This analysis can predict the product a customer is likely to buy next (Dyché and Wesley, 2002). Other advantages of SPA are summarised in Table 2.9. The disadvantage of most algorithms is the combinatorial explosion of sequencing possibilities. There exist hundreds of thousands of items and thus more pairing possibilities. In practice this will relate to a high volume of data and for that *Big Data Analytics* (BDA) might be the only solution. BDA is explained in Subsection 2.8.3. Appropriate techniques identified by Chapman et al. (2000) are correlation analysis, regression analysis, association rules, Bayesian networks, inductive logic programming and visualisation techniques.

The necessary fields are almost the same as with the MBA, namely the content fields, the analysis field and the time field. The content field presents the occurrence of the event. So in the case of the transactional data it is the products purchased. The analysis field is either the customer ID or the transactional ID, depending on the level of analysis. The only part that is extra when looking at the SPA fields is the time field, which is crucial since it represent the acquisitions that took place during a certain time period (Mooney and Roddick, 2013; Tsiptsis and Chorianopoulos, 2009).

Table 2.10: Customer transaction dataset (Mooney and Roddick, 2013).

Customer_ID	Transaction Time	Items Bought
1	June 25 '03	30
1	June 30 '03	90
2	June 10 '03	10, 20
2	June 15 '03	30
2	June 20 '03	40, 60, 70
3	June 25 '03	30, 50, 70
4	June 25 '03	30
4	June 30 '03	40, 70
4	July 25 '03	90
5	June 12 '03	90

Table 2.11: Customer sequence dataset (Mooney and Roddick, 2013).

Customer_ID	Customer Sequence
1	((30)(90))
2	((10 20) (30) (40 60 70))
3	((30 50 70))
4	((30) (40 70) (90))
5	((90))

The first Apriori algorithms (AprioriAll, AprioriaSome, DynamicSome) introduced had a five-step process and are explained with an example (Agrawal and Srikant, 1994; Bounsaythip and Rinta-Runsala, 2001; Mooney and Roddick, 2013):

1. *Sort Phase*: This phase transforms the original dataset to a customer sequence dataset by sorting data by customer_id and then the time stamp. This can be seen in Table 2.10 and Table 2.11.

2. *Large item set Phase*: This phase finds all the large item sets with length one. The length of a sequence is the number of item sets in the sequence. A sequence of length k is called a k-sequence. This is shown in Table 2.12 where a minimum support of 25% was given and the information in Table 2.11 is used.

3. *Transformation Phase*: Each customer sequence is transformed by replacing each transaction with the set of large item sets contained in that transaction. The transactions which do not contain any large item sets are not kept and any customer sequences that do not contain any large item sets are removed. See Table 2.13 for the transformed information.

Table 2.12: Large item set and a possible mapping (Mooney and Roddick, 2013).

Large Item sets	Mapped to
(30)	1
(40)	2
(70)	3
(40 70)	4
(90)	5

Table 2.13: Transformed dataset (Mooney and Roddick, 2013).

C_ID	Original Customer Sequence	Transformed Customer Sequence	After Mapping
1	((30)(90))	({(30)} {(90)})	({1} {5})
2	((10 20)(30)(40 60 70))	({(30)} {(40),(70),(40 70)})	({1} {2, 3, 4})
3	((30 50 70))	({(30)} {(70)})	({1} {3})
4	((30) (40 70) (90))	({(30)} {(40),(70),(40 70)} {(90)})	({1} {2, 3, 4} {(5)})
5	((90))	({90})	({(5)})

4. *Sequence Phase*: In this phase the large item sets are mined to discover frequent sub-sequences. Agrawal and Srikant (1994) states algorithms for these purposes. The algorithms mentioned make multiple passes over the data. The first pass determines the large (*i.e.* minimum support) item sets. The following passes are started with a seed set which was found to be large in the previous pass. This seed set is used to generate a new potential large item set, called candidate sets. The support for these sets is counted during the pass over. At the end of the pass over the actual large item sets are determined and are used as the seed for the next pass. This is done until no new large item sets are found. The Apriori Candidate Generation algorithm consists of the *join* step and then the *prune* step where item sets are deleted if they are not a sub-sequence of the large item set. Please refer to Agrawal and Srikant (1994) for algorithms and examples.

5. *Maximal Phase*: This phase is employed to find all the maximal sequences in the large item sets. Some algorithms incorporate this step in the sequence phase, nevertheless, this phase is applicable in all the algorithms. The algorithms that combine these steps save time by not counting the non-maximal sequences.

These algorithms still had some limitations and in the seminal work of Mooney and Rod-

dick (2013), a summarised table shows some improved algorithms. This summary can be seen in Table 2.14.

Table 2.14: Summary of Apriori-based algorithms (Mooney and Roddick, 2013).

Algorithm name	**Author**	**Notes**
Candidate Generation: Horizontal Database Format		
Apriori (All, Some, Dynamic Some)	Agrawal and Srikant (1995)	
Generalised **S**equential **P**atterns (GSP)	Srikant and Agrawal (1996)	Max/Min Gap Window Taxonomies
PSP	Masseglia et al. (1998)	Retrieval optimisations
Sequential **P**attern m**I**ning with **R**egular ex-press**I**on cons**T**raints (SPIRIT)	Garofalakis et al. (1999)	Regular Expressions
Maximal **F**requent **S**equences (MFS)	Zhang et al. (2001)	Based on GSP uses Sampling
Regular **E**xpression-**H**ighly **A**daptive **C**onstrained **L**ocal **E**xtractor (RE-Hackle)	Albert-Lorincz and Boulicaut (2003a) Albert-Lorincz and Boulicaut (2003b)	Regular Expressions similar to SPIRIT
Maximal **S**equential **P**atterns using **S**ampling (MSPS)	Luo and Chung (2004)	Sampling
Candidate Generation: Vertical Database Format		
Sequential **PA**ttern **D**iscovery using **E**quivalence classes (SPADE)	Zaki (2001)	Equivalence Classes
Sequential **PA**ttern **M**ining (SPAM)	Ayres et al. (2002)	Bitmap representation
LAst **P**osition **IN**duction (LAPIN)	Yang and Kitsuregawa (2005)	Uses last position
Cache-based **C**onstrained **S**equence **M**iner (CCSM)	Orlando et al. (2004)	k-way intersections cache

Continued on next page

Table 2.14 continued

Algorithm name	**Author**	**Notes**
Index **B**it **M**ap (IBM)	Savary and Zeitouni (2005)	Bitmap Sequence Vector Index, NB table
LAst **P**osition **IN**duction **S**equential **PA**ttern **M**ining (LAPIN-SPAM)	Yang and Kitsuregawa (2005)	Bitmap Uses SPAM uses last position

The problem with the Apriori algorithms is their scalability. The improved algorithms alleviate this problem, but the candidate generation and prune method is still inadequate when large datasets are used. This gave rise to the *frequent pattern growth* domain and FP-Growth algorithm. Frequent pattern growth is a method of mining frequent item sets without candidate generation. The original transaction database is compressed in a compact data structure (FP-tree) resulting in greater efficiency (Han and Pei, 2000; Kamber et al., 2012). Mooney and Roddick (2013) listed algorithms for frequent pattern growth and these algorithms are summarised in Table 2.15.

Table 2.15: Summary of pattern growth algorithms (Mooney and Roddick, 2013).

Algorithm name	**Author**	**Notes**
Pattern Growth		
FREquE**n**t pattern-projected **S**equential **PA**tter**N** mining (FreeSpan)	Han et al. (2000)	Projected sequence database
PREFIX-projected **S**equential **PA**tter**N** mining (PrefixSpan)	Han et al. (2001)	Projected prefix database
Sequential pattern mining with **L**ength-decreasing su**P**port (SLP Miner)	Seno and Karypis (2002)	Length-decreasing support

This concludes the basic literature on SPA. This type of analysis can be beneficial in this study and frequent pattern growth will be more appropriate based on scalability, since this study involves a large amount of data. SPA is important in this study because the proposed model must analyse customers' transactional data and identify the sequence in which customers acquire certain products in order to identify the appropriate time to propose a personalised discount offer. In the following section Acquisition Pattern Analysis (APA) is investigated.

2.6.4 Acquisition Pattern Analysis

Acquisition Pattern Analysis (APA) was first proposed as a similar concept to those of the MBA by McFall (1969). Another interpretation of APA was done by placing the focus on

the sequence in which acquisitions are made rather than the composition of the item set. This lead to the same idea as the SPA. A third definition of the APA was suggested by combining the MBA and the SPA to reach the fundamental goal of the APA and relationship marketing, to identify the needs of a customer in order to ensure their satisfaction by making recommendations on marketing activities (Paas et al., 2005).

APA investigates the acquisition pattern of products in order to forecast future acquisitions (Paas and Molenaar, 2005). APA is relevant in industries where a customer has various objectives but due to financial constraints, they cannot be fulfilled. On this aspect, APA is differentiated from the previously discussed section. APA is mostly considered for the durable goods and financial sector services (Paas, 1998; Paas and Molenaar, 2005). APA is advantageous for increasing customer retention and cross-selling opportunities in these respective markets.

Previous studies of APA were usually done on survey data. Paas (2009) conducted research to investigate if APA can be applied to transactional data as well. The research shown that transactional data can also be used for APA in the financial industry. The research unfortunately did not determine if this is the case for durable products as well. The challenge for this study is to determine whether the APA can only be used for durable goods or if it can be used for *Fast Moving Consumer Goods* (FMCG).

Paas et al. (2005) proposed two consecutive steps that the APA should consist of: (1) the definition of the product set, and (2) the investigation of the order in which the products are acquired for each product set. The sequence of these steps is crucial as important information will be lost if the order is reversed. In this research the authors empirically showed how these two steps are executed to combine both the MBA and the SPA.

Mokken scaling is mostly used in literature for APA and also in the research of Paas et al. (2005). Mokken scaling introduces a step-wise approach which insures that vital information is not lost. The model separates the tests by allocating items to item sets and by investigating the sequence in which customers purchase the products. The other available techniques do not include the step-wise approach. Other modelling techniques for APA are Purchase Trees, Guttman Scaling, Parametric Scaling, Latent Class Analysis. The reader is referred to Paas (1998), Paas and Molenaar (2005), Paas et al. (2005), Salazar et al. (2007) for information regarding association rule mining and MBA.

For cross-selling and upselling opportunities the repurchasing behaviour of a customer is important. In the research of Salazar et al. (2007), the authors state two aspects important for repurchase behaviour. The first is the acquisition pattern of the customer and the second is the factors that have the greatest influence on repurchase behaviour. The latter is explained in Subsection 2.6.5.

This subsection illustrated how acquisition patterns can be found, but it is mostly limited

to the financial services market and durable goods. This provides the opportunity to determine if it can be applied for FMCG along with other analyses such as the MBA, SPA and survival analysis, discussed next.

2.6.5 Survival Analysis

Harrell (2015) describes the use of *survival analysis* as the analysis of data in which the time of a specific occurrence is of interest. This can be failure time, survival time or event time. Survival analysis techniques are well established in the domain of healthcare. The techniques are designed to predict the probability that a patient, who is undergoing medical treatment, will survive until time t (Harrell, 2015; Kamber et al., 2012). However, survival analysis can also be applied in the CRM domain.

As mentioned in Subsection 2.6.4, there are factors that have an impact on the repurchase behaviour of customers. These can be customer satisfaction, brand commitment and purchase experience. In the study by Salazar et al. (2007), survival analysis is used to address this aspect of repurchase behaviour. Within the survival analysis domain, there are numerous techniques to be used in different scenarios. For the purpose of repurchasing behaviour it is found that the best choices are Cox regression and binary logic regression (Salazar et al., 2007).

Since the sequence of customer acquisitions has already been investigated by the preceding sections and survival analysis introduces the factors responsible for repurchasing, the only part to discuss is when the next purchase will occur. It is of utmost importance to estimate the appropriate time to offer the most favourable product to the customer. This will ensure that marketing opportunities are fully utilised.

A time sequence is introduced to address this problem. This analysis focuses on *when* the next occurrence and in the case of this study, the next transaction will take place. The two main aspects are the fact that a repurchase will happen and the time period in which it is most likely to happen. This information can be derived from the survival analysis done earlier. One of the outputs from the survival analysis is the survival curve which plots the probability of a repurchase against time. This can be used to estimate when a repurchase might take place (Salazar et al., 2007).

The Cox proportional hazard model is one of the popular techniques along with the Kaplan-Meier estimate (Kamber et al., 2012). The advantages of the Cox proportional hazard model is summarised by Larivière and Van Den Poel (2005) as:

i. It allows for incorporating time-varying covariates and both discrete and continuous measurements of event times.

ii. It can handle observations that did not experience the event.

iii. It appears to be robust and requires few assumptions.

The Cox proportional hazard for customer n at time t, given his vector of covariates x_n can be written as

$$h_n(t, x_n) = h_0 \exp(\beta x_n)$$

in which h_0 represents the baseline hazard.

A disadvantage overlooked is the assumption of proportionality. Proportionality indicates that the hazard for any individual i is a fixed proportion γi_j of the hazard of any other individual where

$$\gamma i_j = \frac{h_i(t, x_i)}{h_j(t, x_j)} = \frac{h_0 \exp(\beta x_i)}{h_0 \exp(\beta x_j)} = \exp\left\{\beta(x_i - x_j)\right\}.$$

In the case where proportionality is violated another technique must be used. Survival forests are used in the research of Larivière and Van Den Poel (2004, 2005).

Trigger events happen within a customer's life cycle and allow the company to predict the future behaviour of a customer (Malthouse, 2007). The Cox proportional hazard model and discrete-time models facilitate time-dependent covariates. Trigger analysis is differentiated whether trigger events only happen at time 0 or are they repeated events. In the case of transactional data, trigger events are repeated and are an option for the Cox proportional hazard model. Trigger events are used for loyalty programmes, financial services, retail websites, *etc.* (Malthouse, 2007).

Another popular technique for estimating survival is the Kaplan-Meier estimator, which is a non-parametric estimator (Bland and Altman, 1998). The probabilities of survival are presented in a survival curve, where the graph is a step function. Sudden changes in the estimated probability corresponds to the time at which the events happen (Larivière and Van Den Poel, 2005; Rosset et al., 2003). Harrell (2015) can be used as reference to illustrate in detail how the Cox proportional hazard model, Kaplan-Meier estimator and other techniques are defined.

Table 2.16 displays references to literature where survival analysis has been used.

This section provided an overview of the analysis needed to estimate the time of the next repurchase. This, along with the APA, which indicates the sequence of acquisitions, provides marketers with the knowledge to create cross-selling and upselling offers to customers. The researcher finds that in the case of this particular study and scenario, a combination of these analysis methods must be used to obtain the goal of the proposed model. This next section presents a holistic view of Big Data and explains when a dataset is considered Big Data.

Table 2.16: Survival analysis applications

Domain	Industry	Technique	Reference
CRM (Customer complaint behaviour)	Financial	Cox proportional hazard Survival trees	Larivière and Van Den Poel (2005)
CRM (Customer churn and choice modelling)	Financial	Kaplan-Meier estimates Proportional hazard	Larivière and Van Den Poel (2004)
CRM (Customer Lifetime Value)	Retail Hospitality	Cox proportional hazard	Malthouse (2007) Rosset et al. (2003)
Marketing	Retail Service providers	Cox proportional hazard	Malthouse (2007)

2.7 Big Data

Big Data [1] is one of the new important concepts within the industry of information and technology. In the following section, an overview of Big Data is given along with the characteristics which describe Big Data. The overview provides a prospective definition of Big Data and sheds light on when data are considered Big Data. The characteristics of Big Data are explained in great detail to shed light on the different attributes of Big Data. This section is important as this is the data that are used in this study.

2.7.1 Overview of Big Data

The term Big Data has been used more frequently during the past few years. Researchers can still not give an acceptable definition for this term.

Most sources define Big Data by reviewing the Vs, which are the characteristics of Big Data. The three main characteristics are *Volume, Velocity and Variety*. Some sources add Veracity, Value and Variability to these to define Big Data (De Mauro et al., 2016; Demchenko et al., 2014; Gandomi and Haider, 2015; Zikopoulos et al., 2013). The characteristics are explained in more detail in Subsection 2.7.2.

Demchenko et al. (2014) argue that the Vs only refer to the properties of Big Data. In order to define Big Data as a new technology, the definition must be improved and extended to highlight all the important features and related infrastructure components. This is done by describing Big Data as having five parts. This is visualised in Figure 2.10.

The first part is the characteristics that describe Big Data (some sources refer to the 3Vs; others mention even more Vs). Secondly, new data models are created by using data linking and the constant changes while processing data. In order to analyse these new data models

[1] The term Big Data is treated as a singular; it is considered a mass noun in this thesis.

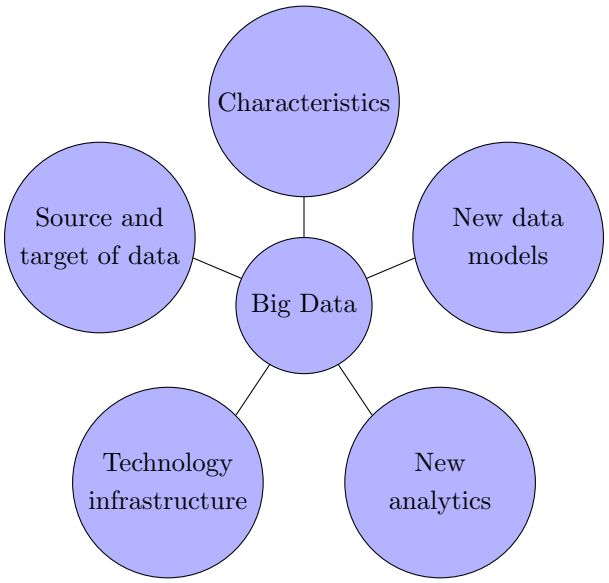


Figure 2.10: Big Data definition

the third part of the Big Data technology comes into play. New analytics must be used such as streaming analytics and machine learning, because the ordinary data analytics are inadequate to handle such large amounts of data.

The fourth element is the infrastructure that needs to be altered in order to accommodate the changes imposed by the previously mentioned parts. This is done by using new technology such as cloud-based infrastructures and high performance computing. The last important aspect is the source and target of the data. Data is being captured at a high velocity from a variety of sources and must be delivered to different systems or consumers. A ubiquitous technological network is necessary to ensure the data are captured and delivered correctly.

The researcher has concluded that the above-mentioned information and infrastructure components must be taken into consideration when deciding to venture into Big Data and Big Data Analytics (BDA). This still does not give a concise definition of what Big Data is, but more defines Big Data technology and what might be necessary to analyse data in the future.

De Mauro et al. (2016) conducted research on the occurrence of Big Data-related terms from various scientific papers and found that there exist four fundamental themes: information, technology, methods and impact. By using existing definitions, they could classify them into four groups according to the focus of the definition. These groups were: Attributes of Data, Technology needs, Overcoming of thresholds and Social impact. It was clear that some definitions contained some fundamental themes that were identified earlier. De Mauro et al. (2016) proposed a new definition that joins the existing definitions and fundamental themes:

"Big Data is the Information asset characterised by such a High Volume, Velocity and Variety to require specific Technology and Analytical Methods for its transformation into Value."

Understanding the importance of Big Data is often more important than understanding

the definition of Big Data. Zikopoulos et al. (2013) state: "Big Data is all about better analytics on a broader spectrum of data, and therefore represents an opportunity to create even more differentiation amongst industry peers." Big Data ultimately entails the storing of large volumes of data, which does not mean anything. By using analytics, these large information sets are converted into something of value to the enterprise and thus create a competitive advantage. It is clear that using Big Data can be beneficial to a company. This does not mean that a company that does not apply BDA will be unsuccessful. Enterprises can use data analytics that is compatible with the data they have and their strategies.

Considering the different views on the definition of Big Data, the researcher agreed that the features and components mentioned by Demchenko et al. (2014) are also, broadly speaking, part of the concise definition proposed by De Mauro et al. (2016). The researcher insists that only when data fulfil the themes and definition as mentioned by De Mauro et al. (2016), can it be considered as Big Data.

2.7.2 Big Data Characteristics

This section describes the characteristics of Big Data. The three main characteristics that are highlighted in literature are Volume, Velocity and Variety, as mentioned before. Along with these, some sources also list other characteristics that are explained in this section.

Volume is probably the most important characteristic of all. Volume refers to the magnitude of data and normally implies an enormous amount of data that are generated and stored. The core idea of volume stays the same over time, but the definition may vary as time passes. Before 2010 data measured in petabytes(Pb) would be considered as Big Data. Today, experts already consider Big Data to be measured in zettabytes(Zb). This shows that technological intelligence improves each year and the threshold for Big Data changes frequently.

Along with volume the type of data, which is explained under the Variety characteristic, also plays a role in the threshold of Big Data volume. Datasets of the same size, but different types, may require alternative analytics. The one dataset may be considered as Big Data and the other one not, even though they are the same size (Gandomi and Haider, 2015; Lakshmi Prasad, 2016; Zikopoulos et al., 2013).

Velocity of data and more in particular Big Data is the rate at which data are generated or received. But along with this, velocity is also the rate at which data are analysed to be of value for the enterprise (Gandomi and Haider, 2015; Zikopoulos et al., 2013). The velocity of data is increasing drastically with the proliferation of digital devices. Erl et al. (2015) state that the velocity of data may vary and may not always be as high. The velocity of the data must be put in perspective with the data source that creates the data. This is described by considering Figure 2.11 that shows how the different sources easily create data volumes in a given minute. The researcher noticed the importance of velocity in the sense of analysing data,

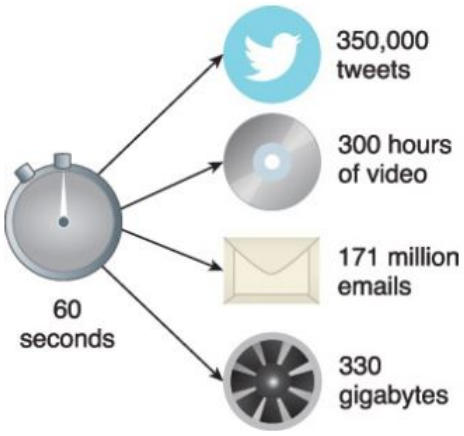


Figure 2.11: Examples of high-velocity Big Data datasets produced every minute include tweets, video, emails and Gbs of diagnostic data generated from monitoring a jet engine (Erl et al., 2015).

since data arriving is only of value to the enterprise after the analysis thereof. Technology utilised for BDA must ideally be able to process and analyse data at a higher velocity than that at which the data are received. Unfortunately this is not the case in the real world.

Variety of data refers to the heterogeneity of datasets. Datasets can be categorised by being structured, semi-structured or unstructured. Structured data are typically tabular data found in spreadsheets or relational databases (Gandomi and Haider, 2015). Another example of structured data is financial transactions (Erl et al., 2015). Unstructured data are data such as images, videos and audio files that do not have any fixed structure. Unstructured data can contain textual and numerical data as well. These types of data structures are often inadequate to be analysed by machines (Gandomi and Haider, 2015). Lastly, semi-structured data falls between structured and unstructured data. Examples of semi-structured data are emails, tweets and user reviews (Lakshmi Prasad, 2016). For the purpose of this study, the data used will be of a structured nature. Zikopoulos et al. (2013) expect data variety to expand as time passes, which means new analytical methods must be discovered or created in order to use all types of data structures. Using advanced analytics and combining structured and unstructured datasets will result in a more personalised result with greater insights.

Veracity is becoming more important when referring to Big Data. Veracity refers to the quality and trustworthiness of data (Zikopoulos et al., 2013). Data are often entered incorrectly which creates noise within the dataset. This results in the need to assess data and clean it before analysis can commence. Noise in a dataset is data that cannot be analysed and cannot be converted into information. Such data has no value. The part of a dataset that can be analysed is the signal part of the dataset. If the signal-to-noise ratio of a dataset is high, the dataset has a higher veracity. Veracity increases as the number of data sources increases and the signal-to-noise ratio is also dependent on the source and the type of data

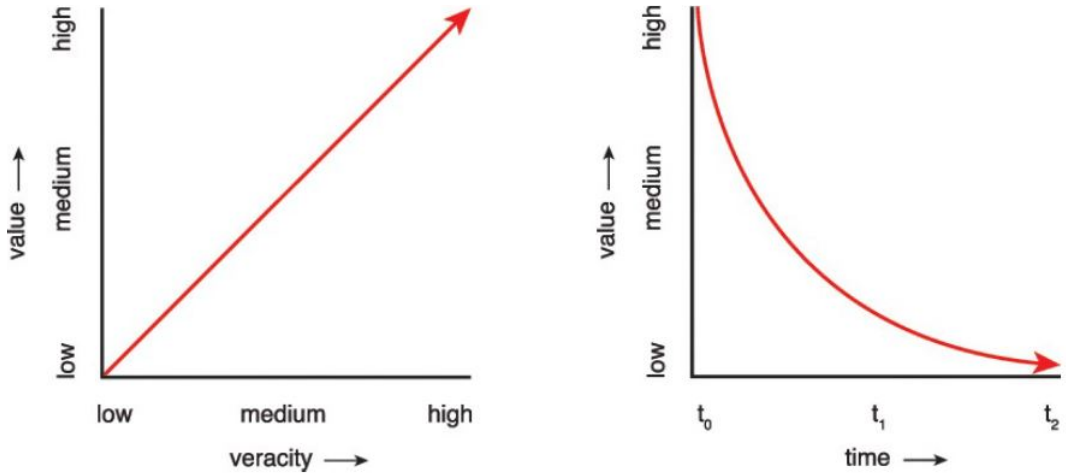


Figure 2.12: Data that has high veracity and can be analysed quickly has more value to a business (Erl et al., 2015).

being captured (Erl et al., 2015).

Value is one of the newer Vs when describing Big Data. Rajaraman (2016) states that data by itself has no value unless it is processed. Value is defined by Erl et al. (2015) as the usefulness of data for an enterprise. This characteristic is intuitively related to the veracity characteristic. A dataset that has a high veracity (thus is more trustworthy) has higher value to the enterprise. Apart from the value the data has for the enterprise, value is also dependent on the time it takes to analyse a dataset. Value and time are inversely related. Figure 2.12 visualises the relationship between value and time and between time and veracity.

Variability refers to the variation in the flow rate of data. This is in relation with the velocity characteristic. Big Data velocity may be inconsistent and have periodic peaks that can influence the quality of analysis (Gandomi and Haider, 2015).

Volatility characterises how long the data is valid (Lakshmi Prasad, 2016). This can have an influence on the results obtained as data that is valid at a certain point in time may not be valid after a few hours or days. This characteristic will depend on the reason for the data being analysed and what must be accomplished with the results.

The researcher argues that there are 4Vs necessary to define Big Data. These characteristics are Volume, Variety, Velocity and Veracity. The other Vs mentioned in this section are related to these four main Vs and not necessarily one of the core characteristics. The researcher is concerned that the Value characteristic is not necessarily a characteristic of Big Data but mostly a derivative thereof. The value of data cannot always be seen before the analysis is done. Data needs to be analysed to be of value.

Different analytical methods are available to analyse data and in this case Big Data. The following section illustrates some tools and techniques as well as major analytical processes used for analysing data.

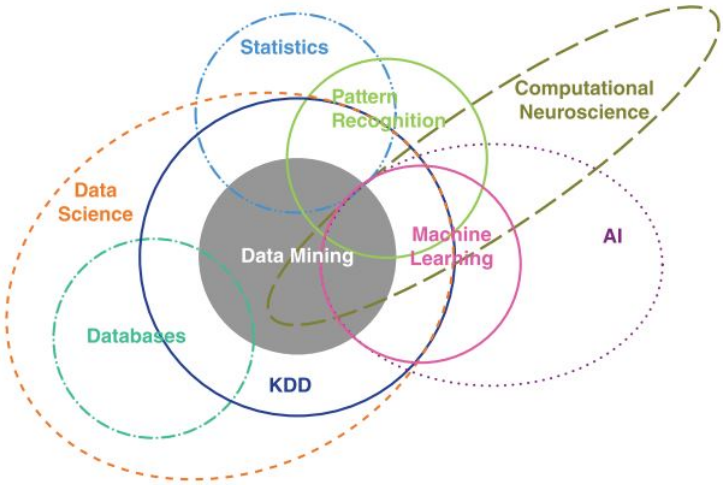


Figure 2.13: Multidisciplinary nature of data mining (Dean, 2014).

2.8 Big Data Analytics

Analytical methods are needed to extract unknown knowledge from large datasets which cannot be recognised by a human being. Data mining is the process used to analyse datasets described in the preceding sections. Previous academic literature delivers a wide variety of methods and techniques available to analyse datasets described in Subsection 2.7.2. The detailed explanation of the different processes, methods, tools and techniques was not provided in previous sections, and will therefore be the focus of this section.

2.8.1 Overview of Big Data Analytics

A variety of data mining tools are available. Each of these tools are designed to analyse a certain type of data. These tools can also be used in conjunction with each other and it is here where some people get confused between the different terminology and the use thereof. Figure 2.13 from Dean (2014) illustrates the inter-connection between the different types of analysis and knowledge areas.

This study has a focal point within the combined area of data mining, knowledge discovery in databases (KDD), machine learning, artificial intelligence (AI) and pattern recognition. Within literature, these terminologies have sometimes been used in a confusing and overlapping way. Thus, the researcher compiled a high level diagram of BDA as part of USMA (2017). This diagram can be viewed in Figure 2.14.

BDA is composed of different processes which provide a methodology to analyse data. The processes encompass a finite number of steps or phases, of which data mining is one.

Data mining is the physical process of discovering patterns and gaining knowledge from

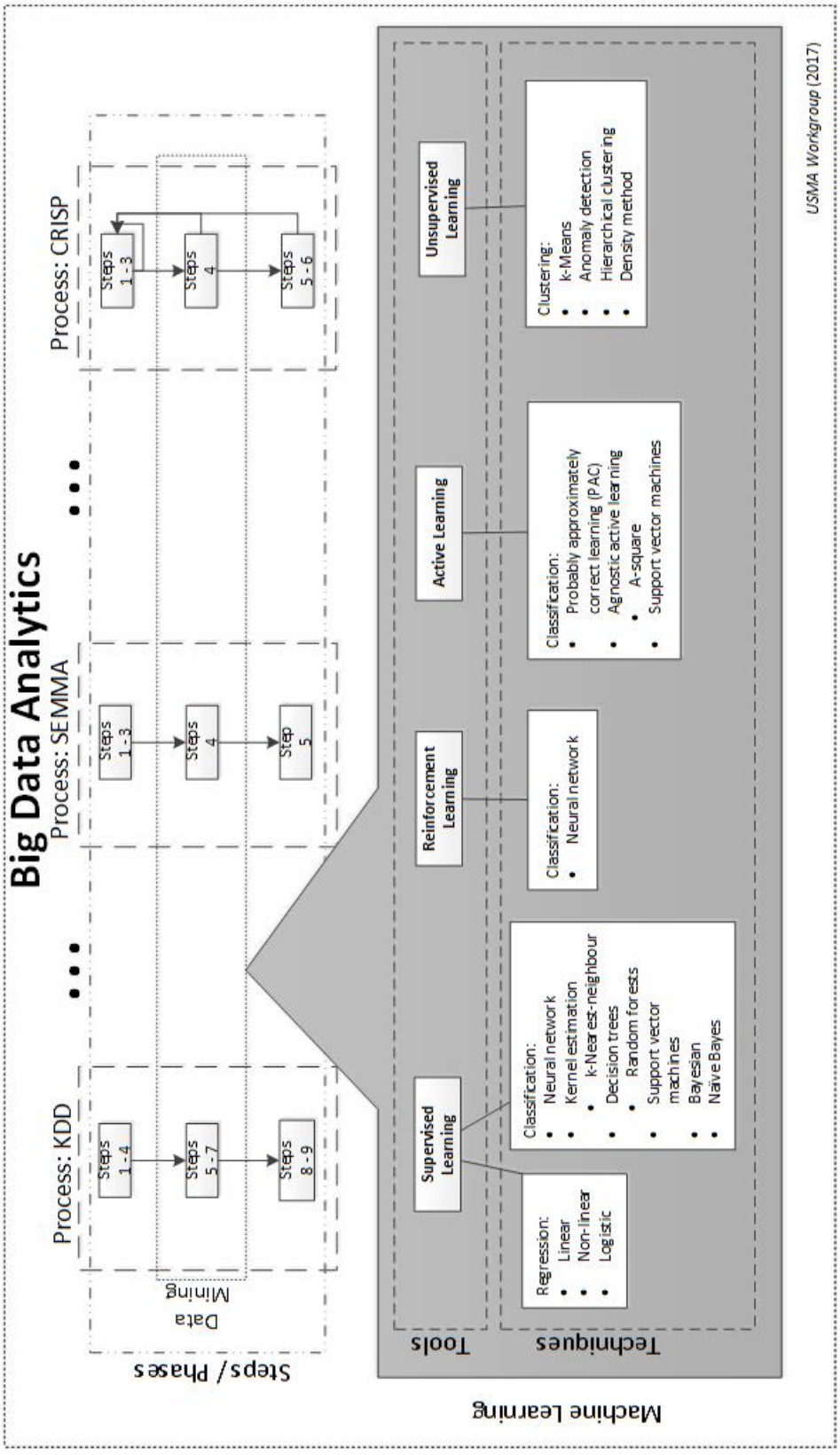


Figure 2.14: Big Data Analytics (USMA, 2017).

large datasets as described in Section 2.1 and Section 2.6 (Kamber et al., 2012). This is a dynamic and iterative process where previously unknown comprehensible knowledge is extracted from the datasets (Dean, 2014; Lanjewar and Yadav, 2013; Ngai et al., 2009). Data mining can be applied to any dataset and is thus a very broad term. Data mining is used to complete certain core CRM activities (cross-selling and upselling, retention management) identified in Section 2.1.

When looking at data mining methods to analyse Big Data, machine learning is one of them. Bauckhage et al. (2007) see machine learning as the mimic of flexible learning capabilities of the human brain. It is the area within computer science where the utilisation of tools and techniques provide computers with the ability to learn without being explicitly programmed (Rajaraman, 2016). Computers are programmed in order to learn from given data. The experience gained from the data is used to investigate unknown data and identify useful information (Ben-David and Shalev-Shwartz, 2014). Machine learning algorithms perform better with regard to speed and capacity when analysing large datasets, than statistical techniques (Tsiptsis and Chorianopoulos, 2009).

Different machine learning algorithms are categorised based on the output wanted from the data being analysed. This leads to different types of learning tools namely: Supervised Learning, Unsupervised Learning, Reinforcement Learning and Active Learning, shown in Figure 2.14. The different types of machine learning tools and their subsequent techniques are explained in Subsection 2.8.3.

2.8.2 Big Data Analytic processes

Arguably the three best-known Big Data Analytic processes available in literature are used in the construction of the diagram in Figure 2.14 and are shortly explained in this section.

KDD is known as the *Knowledge Discovery from Databases*. Fayyad (1996) formulated a high-level definition of KDD as Knowledge Discovery in Databases in the non-trivial process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data. Several researchers (Azevedo and Santos, 2008; Kamber et al., 2012; Mansingh et al., 2013) simplified the KDD process developed by Fayyad (1996) to only the data mining tasks. The researcher is of the option that the nine steps identified by Fayyad (1996) exhaustively explain the overall KDD process. The nine steps are discussed in Table 2.17. Figure 2.15 gives a visual presentation of the entire KDD process.

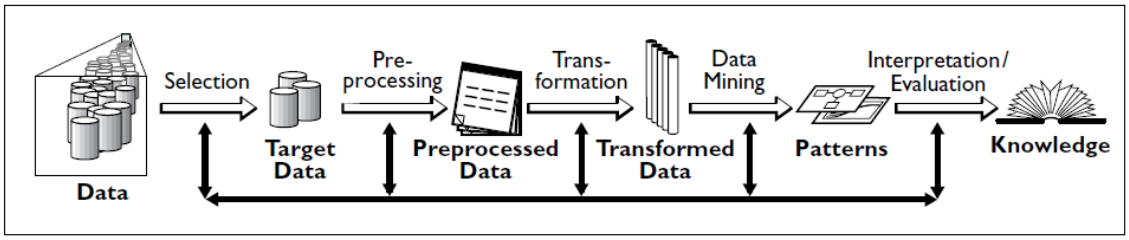


Figure 2.15: Overview of the KDD process (Mariscal et al., 2010).

SEMMA is a process developed by the SAS Institute, which is a step-by-step guide for the data mining process. SEMMA is used within the Enterprise miner software created by the SAS Institute. The core data mining processes are carried out by Enterprise miner and SEMMA is seen as their logical organisation and not necessarily a data mining methodology. Enterprise miner can be adopted by any individual as part of a data analytics project (Dean, 2014). The acronym SEMMA identifies the five stages of the data mining process (Sample, Explore, Modify, Model and Asses) as established by the SAS Institute.

1. Sample – Extracting a portion of data from a dataset large enough to hold significant information, yet small enough to utilise rapidly.

2. Explore – Searching for unanticipated patterns and anomalies in data. This can include visual exploration or other techniques such as clustering.

3. Modify – Data are modified by creating, selecting and transforming variables. This is done to focus on the model selection process.

4. Model – The data are modelled by using software to automatically search for a combination of data which predicts a desired outcome. Modelling techniques are explored further in Subsection 2.8.3.

5. Assess – Evaluate the reliability of the outcomes from the previous step. This can be done by introducing sample data in Step 1.

CRISP-DM is a methodology proposed by a group of industry leaders involved in data mining. CRISP-DM, short for Cross-Industry Standard Process for Data Mining, is a reference guide that is industry-, tool- and application neutral. The methodology is explained by a hierarchical process model with four levels of abstraction.

The data mining process (top level) is organised in different phases which each contain several second-level generic tasks. The second level holds the generic task and can be applied to multiple data mining situations. The third level is more specialised and describes how the generic task will be executed in a specific scenario. Lastly, the fourth level records the actions,

Table 2.17: KDD process, adapted from Fayyad (1996) and Mariscal et al. (2010).

Steps	**Explanation**
1. Understanding of the application domain.	Developing an understanding of the relevant prior knowledge, and the goals of the end user. This step is dependent on the user.
2. Target dataset.	Creating or selecting a dataset, or focusing on a subset of variables or data samples, on which discovery is to be performed. This includes homogeneity of data, dynamics, changes over time, sampling strategy, *etc.*
3. Data cleaning and preprocessing.	This step includes basic operations such as: Removal of noise and outliers, Collecting information to account for noise, Strategies for missing data fields, *etc.*
4. Data reduction and transformation.	Exploring useful features to represent data. Dimensionality reduction/transformation methods to reduce number of variables under consideration. Projecting data to spaces where solutions are easier to find.
5. Choosing the data-mining task or function.	This step includes deciding on the model purpose of the model and the goal of the data mining functionality (*e.g.* Classification, regression, clustering, *etc.*)
6. Choosing the data-mining algorithms(s).	The selection of techniques to be used for identifying patterns or fitting models to the data. The choice of appropriate models and parameters is critical.
7. Data mining.	This is the physical step of searching for hidden patterns in data.
8. Evaluating output of Step 7.	The interpretation of the results from Step 7 and deciding if the outputs are deemed knowledge. The outcome of this step might require alterations in previous steps and restarting the whole process.
9. Consolidating discovered knowledge.	Incorporating the knowledge into the performance system, taking action based on the knowledge found or simply documenting it and reporting it to users. This step also includes identifying potential conflicts with previously believed/extracted knowledge.

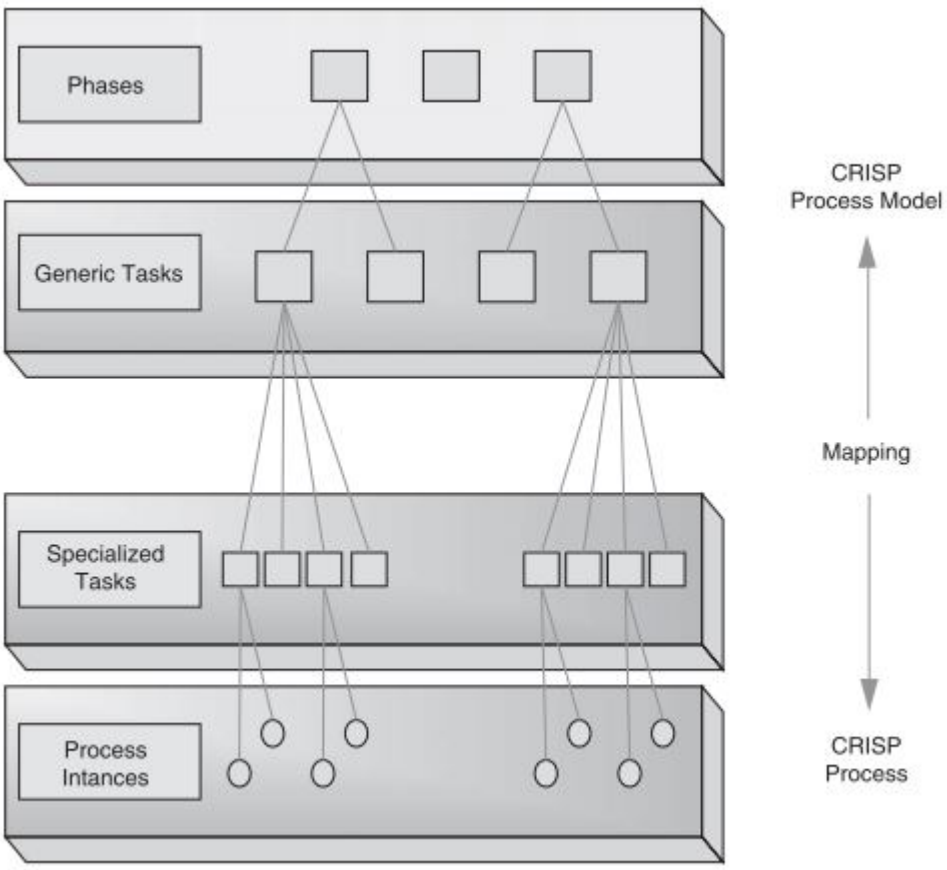


Figure 2.16: CRISP-DM process model methodology (Chapman et al., 2000).

decisions and results of the actual data mining engagement. This level is called the process instances. Figure 2.16 visually explains the hierarchical process model of the CRISP-DM methodology.

On a horizontal level the CRISP-DM methodology differentiates between a reference model and a user guide. The reference model describes what to do by presenting an overview of the phases, tasks and their outputs. Whereas, the user guide explains how to do it by giving more detail for each phase and task. An in-depth explanation of the reference model and user guide can be found in the report of Chapman et al. (2000).

The different phases of the reference model represent the life cycle of the data mining project as shown in Figure 2.17. The phases are not sequential and it is required to move back and forth between the phases, because as previously mentioned, data mining is an iterative process.

Business understanding is essentially understanding the objectives and requirements of the project and defining an appropriate problem definition for the project. *Data understanding* is the first encounter with the data and includes activities such as data collection, identifying data quality and detection of interesting hidden information. The *data preparation* phase

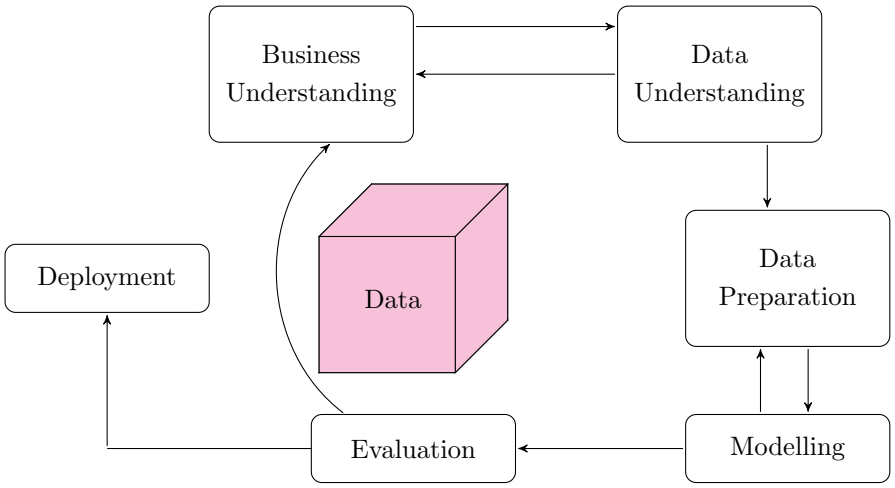


Figure 2.17: CRISP-DM life cycle, adapted from (Chapman et al., 2000).

includes all activities imposed on initial raw data in order to construct the final dataset. During the *modelling phase*, several data mining techniques are applied and their parameters are calibrated to optimal values. At this point a high quality model has been built. Thus, the *evaluation phase* consists of a thorough assessment as to whether the model achieved the desired business objectives. Lastly, the *deployment phase* consists of the activities involved in the organisation and presentation of the gained knowledge (Chapman et al., 2000). Tsiptsis and Chorianopoulos (2009) also explained the CRISP-DM methodology in more detail.

According to Mariscal et al. (2010), CRISP-DM is the most commonly used methodology in practice. However, the use of it has been decreasing because of other in-house methodologies being used such as SEMMA. When comparing CRISP-DM to the KDD process it can be confirmed that the KDD process proposes more specific phases of the data mining tasks. The SEMMA methodology concentrates more on the technical features of the data mining process and does not include the data mining project management phases.

KDD, SEMMA and CRISP-DM were only briefly described in this section. However, these are not the only methodologies available for knowledge discovery. Other known approaches can be found in Mariscal et al. (2010), where some of them build on the principles of the methodologies discussed in this study.

From the research about knowledge discovery methodologies and models, Mariscal et al. (2010) developed a redefined data mining process taking into account the different phases of the known methodologies. Unfortunately, there is insufficient evidence to confirm that this methodology has been tested and works in practice. The following section goes into more depth about the different machine learning tools and techniques identified in Figure 2.14.

2.8.3 Different Big Data Analytical tools and techniques

In this section the researcher continues with the explanation of the BDA diagram in Section 2.8.1. Within the machine learning application, there are a variety of learning tools and techniques that can be used for different types of data. The different tools to be used are based on the various methods of machine learning. Only the fundamentals of machine learning are discussed and references to more detailed literature are provided.

Supervised Learning (SL) is when the model learns from a set of training data, which contains predefined examples. These models require training datasets with historical data and the training data are thus labelled. A target variable is available in the test data and the model must correctly predict or classify the observations. The model is trained with input examples to predict desired output variables. The generated output can be compared with the known correct output. Thus, with supervised learning the analysts know what they are looking for (Agrawal and Srikant, 1994; Bounsaythip and Rinta-Runsala, 2001; Dean, 2014; Kamber et al., 2012; Lakshmi Prasad, 2016; Tsiptsis and Chorianopoulos, 2009).

In contrast to SL, *Unsupervised Learning* (UL) refers to models that do not use training data. The input example datasets are unlabelled and no target variable exist. Thus, there is no distinction between test and training data. The analyst does not know what to look for and needs to find the structure in the data (Dean, 2014; Kamber et al., 2012; Lakshmi Prasad, 2016). Association rule modelling described in Subsection 2.6.2 is an example of an unsupervised technique.

Active Learning (AL) is a method where the user actively participates in the learning process. The user can be prompted to label an example that was part of an unlabelled set. The model acquires knowledge from human users with the goal of optimising the model quality. This happens during the training time of the model (Ben-David and Shalev-Shwartz, 2014; Kamber et al., 2012).

Reinforcement Learning (RL) is explained as mapping situations to actions. Reward and penalty signals are used for evaluating the action of the learner. The learner must discover which action yields the best reward by choosing them but the learner is not told which action to take. This evaluates the learner's response in an initially unknown environment. The goal is to maximise a numerical reward system. This learning method not only affects the immediate step and reward, but also the subsequent rewards throughout the process (Schmidhuber, 2015; Sutton and Barto, 1998).

The various learning methods can be subdivided into different techniques based on the data to be analysed. The technique contains data models and their assorted algorithms as seen in Figure 2.14. The data models (Classification, Clustering, Regression, *etc.*) are created based on the type of patterns that can be found within the data mining tasks. These tasks can be classified into four general types based on the results they contain. The data analytics behind

the categories are aimed at delivering answers to numerous decisions that must be made (Erl et al., 2015; Kamber et al., 2012). The different data analytic types are discussed in Table 2.18.

Table 2.18: Categories of data analytics (Bounsaythip and Rinta-Runsala, 2001; Dyché and Wesley, 2002; Erl et al., 2015; Kamber et al., 2012).

Data analytic type	**Explanation**	**Example**
Predictive	Current data are used to predict the outcome of an event that might occur in the future. The predictions are based on patterns and trends found in historical data.	If the customer purchased product X, what is the chances she will purchase product Y and product Z?
Descriptive	Current data are used to provide information about the relationships within the underlying data. This is used to answer questions based on events that already happened. These analytics characterise the properties of the data.	What was the amount of money the customer spent on a certain product thus far?
Diagnostic	This analysis is aimed at determining the cause or reason behind an event.	Why does the customer buy more shampoo than soap?
Prescriptive	This analysis complements the predictive analysis by prescribing actions that can be taken. It embeds elements of situational understanding and thus provides results that can be reasoned about.	When is the best time to propose a certain offer?
Association	This type of analysis is used to detect similar items or events that occur together.	Associations can be descriptive. This is often applied to Market Basket Analysis.
Sequence	This type of analysis focuses on the sequence in which a combination of events occur.	Sequence analysis can be predictive. This is used for acquisition pattern analysis and sequential pattern analysis.

As mentioned before, a variety of data models exist based upon the patterns that can be found. Thus, a brief discussion of the data modelling types seen in Figure 2.14 is as follows:

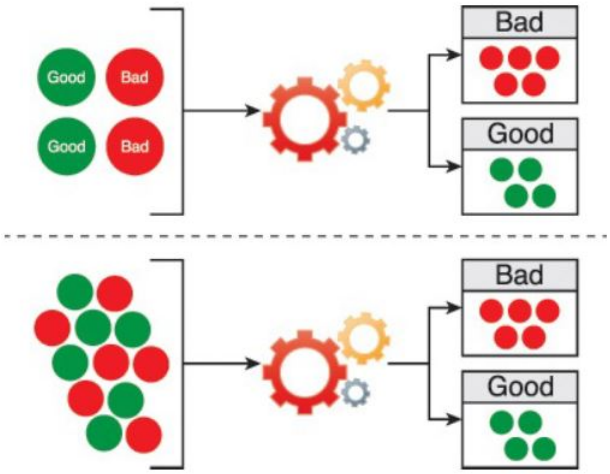


Figure 2.18: Classification example (Erl et al., 2015).

Classification is when data objects are divided into predefined classes with associated class labels and are generalised under a predictive data analysis type. This is considered as a supervised machine learning tool explained by Erl et al. (2015) consisting of two steps:

1. Training data which are already categorised and labelled, are fed into the system. The system develops an understanding of the different categories within the data.

2. Similar but unknown data are fed into the system for classification. The algorithm classifies the unlabelled data based on the developed understanding from the training data.

Kamber et al. (2012) also explain classification by referring to the *learning step* and the *classification step*. Classification can be used for SL, RL and AL machine learning methods. This concept can be easier understood by looking at Figure 2.18.

Here, the top part of the figure represents the training data with the predefined classes. The bottom half of the figure corresponds to the unlabelled data that must be classified into the correct classes. Table 2.19 provides an overview of the various classification techniques, their applications and some resources within literature.

Table 2.19: Classification techniques, compiled by USMA (2017).

Classification			
Technique	**Tool**	**Application**	**Source**
Decision Trees: -Decision Trees -Classification and regression trees (CART) -C4.5 Algorithm -Random Forest	SL	Customer identification Target customer analysis Direct marketing Loyalty programmes One-to-one marketing	Breiman et al. (2017) Kim et al. (2006) Kotsiantis (2007) Tsiptsis and Chorianopoulos (2009) Kamber et al. (2012) Dean (2014) Ben-David and Shalev-Shwartz (2014) Larose (2014) Paramasivam et al. (2014) Rokach and Maimon Hssina et al. (2014) Quinlan (2014) Steynberg (2016) Agarwal et al. (2016)
Support Vector Machines (SVM)	SL AL	One-to-One marketing Text and hypertext categorisation Pattern recognition Bioinformatics	Vapnik (1999) Huang et al. (2007) Kotsiantis (2007) Jansen (2007) Tomar and Agarwal (2013) Dean (2014) Ben-David and Shalev-Shwartz (2014) Rechenthin (2014) Agarwal et al. (2016) Lakshmi Prasad (2016)

Continued on next page

Table 2.19 continued

Technique	Tool	Application	Source
Neural Networks	SL RL	Decision-making Pattern recognition Face identification Sequence recognition Direct marketing Spam filtering Segmentation	Bloom (2004) Chan (2005) Kuo et al. (2006) Izenman (2008) Paliwal and Kumar (2009) Kamber et al. (2012) Dean (2014) Lakshmi Prasad (2016)
Bayesian Network	SL	Direct marketing Pattern recognition Spam filtering Customer lifetime value	Kamber et al. (2012) Rechenthin (2014) Li (2015) Agarwal et al. (2016)
***k*-Nearest Neighbour**	SL	Concept search Recommendation systems Outlier detection Loyalty programmes	Kotsiantis (2007) Salkind (2007) Kamber et al. (2012) Li (2015) Lakshmi Prasad (2016)
Rule-based classifiers	SL	Concept search Recommendation systems Outlier detection Loyalty programmes	Kamber et al. (2012)

Clustering is the process where data objects are divided into multiple different clusters based on characteristics. Data objects within the same cluster have high similarities, but are very dissimilar regarding objects in other clusters (Kamber et al., 2012). This is seen as unsupervised machine learning and aim at finding structure in a dataset with unlabelled data objects (Lakshmi Prasad, 2016).

Clustering is used more to understand the characteristics of data and is considered to be a descriptive type of data analysis. Whereas, classification can be used afterwards to make better prediction about similar unseen data. The main difference between the two types is that at the start time of the algorithm the clusters are unknown (Ngai et al., 2009). Clustering is visually described by Figure 2.19.

Table 2.20 shows the different clustering techniques available along with their applications and relevant literature sources.

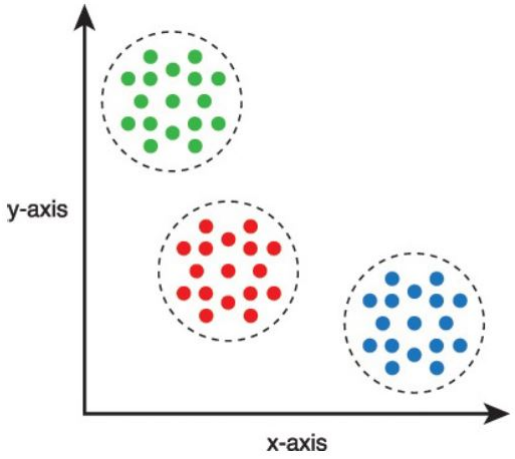


Figure 2.19: Clustering example (Erl et al., 2015).

Table 2.20: Clustering techniques, compiled by USMA (2017).

Clustering			
Technique	**Tool**	**Application**	**Source**
Clustering	UL	Segmentation Product positioning Recommendation systems Selecting test markets object recognition Grouping of items	Aldenderfer and Blashfield (1984) David (2005) Kuo et al. (2006) Jansen (2007) Izenman (2008) Chiu and Tavella (2008) Tsiptsis and Chorianopoulos (2009) Madhulatha (2011) Kamber et al. (2012)
Partitioning (Non-hierarchical) methods: -k–means -k–medoids	UL	Algorithms create single sets of clusters, most effective for small/medium datasets.	David (2005) Jansen (2007) Tsiptsis and Chorianopoulos (2009) Kamber et al. (2012) Lanjewar and Yadav (2013) Dean (2014) Rajarajeswari and Ravindran (2015)
Hierarchical methods: -Divisive (Top down) -Agglomerative (Bottom-Up) -Fuzzy C-Means	UL	Algorithms create separate sets of clusters, each in their own hierarchical level (multiple levels).	Halkidi et al. (2001) Chiu and Tavella (2008) Izenman (2008) Tsiptsis and Chorianopoulos (2009) Madhulatha (2011) Dean (2014)

Continued on next page

Table 2.20 continued

Technique	Tool	Application	Source
Density-based methods: -DBSCAN/ DENCLUE	UL	The key idea is to group neighbouring objects of a dataset into clusters based on density conditions. It grows clusters either according to the density of neighbourhood objects (*e.g.*, DBSCAN) or according to a density function (*e.g.*, DENCLUE).	Kamber et al. (2012)
Grid-based methods: -STING/ CLINQUE	UL	These algorithms are mainly proposed for spatial data mining. Their main characteristic is that they quantise the space into a finite number of cells and then they do all operations on the quantised space.	Bounsaythip and Rinta-Runsala (2001) Kamber et al. (2012)
Self-Organising Maps (SOM)	UL	Target customer analysis Segmentation Complaint management	Bounsaythip and Rinta-Runsala (2001) Tsiptsis and Chorianopoulos (2009)

Regression explores the relationship between a dependent variable and an independent variable within a given dataset (Erl et al., 2015). Regression can also be used to predict a value of a certain variable based on the values of other variables, given a linear or non-linear model of dependency. Regression is a predictive type of data analysis which is the same as classification. The difference is that regression is used for continuous valued variables (Bounsaythip and Rinta-Runsala, 2001). Table 2.21 summarises the various types of regression models, some of their applications and references within literature.

Table 2.21: Regression techniques, compiled by USMA (2017).

Regression			
Technique	**Tool**	**Application**	**Source**
Linear Regression	SL	A model that can show relationships between two variables and how one impacts the other.	Dean (2014) Erl et al. (2015) Ben-David and Shalev-Shwartz (2014) Gera and Goel (2015) Paliwal and Kumar (2009) Yang et al. (2017)
Simple Linear Regression	SL	Evaluate trends Forecasting Analyse marketing effectiveness Assess finance / insurance risks Customer lifetime value	Dean (2014) Erl et al. (2015) Larivière and Van Den Poel (2004) Larivière and Van Den Poel (2005) Ben-David and Shalev-Shwartz (2014) Bishop (2006) Paliwal and Kumar (2009) Salkind (2007)
Multi Linear Regression	SL	The same as with simple linear regression, but with more variations.	Lakshmi Prasad (2016) Bishop (2006) Paliwal and Kumar (2009) Salkind (2007)
Continued on next page			

Table 2.21 continued

Technique	Tool	Application	Source
Non-Linear Regression	SL	Effectiveness of marketing campaigns	Erl et al. (2015) Bates and Watts (2008) Chatterjee and Hadi (2006) Gallant (1975) Gera and Goel (2015) Riffenburgh (2011) Ruckstuhl (2010) Tellis (2006)
Logistic Regression	SL	Loyalty programmes Credit scoring Fraud detection Segmentation Direct marketing	Lakshmi Prasad (2016) Mansingh et al. (2013) Ben-David and Shalev-Shwartz (2014) Salazar et al. (2007) Rosset et al. (2003) Chatterjee and Hadi (2006) Hosmer Jr et al. (2013) Montgomery et al. (2012) Riffenburgh (2011) Salkind (2007)

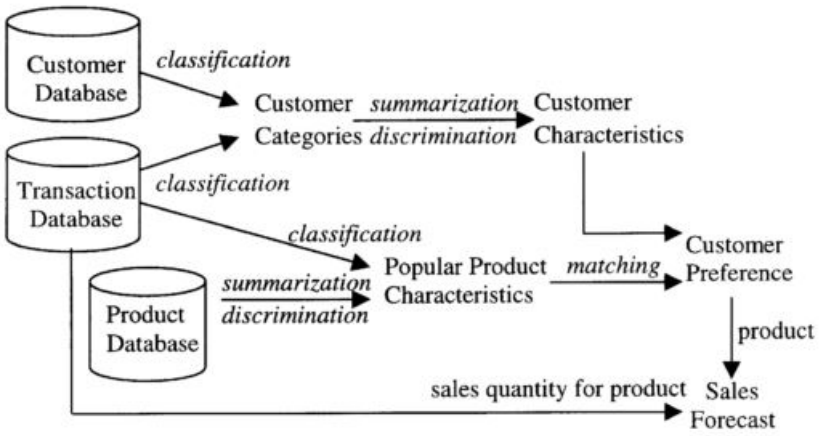


Figure 2.20: Customer profiling system (Shaw et al., 2001).

There exist numerous algorithms that are categorised under the different tools and techniques explained in this section. The few algorithms viewed in Figure 2.14 are only some of the best known ones. The focus of this section is a discussion of the different concepts of BDA. The reader may use the references in Tables 2.19, 2.20 and 2.21 to gain more knowledge about the algorithms mentioned in the BDA diagram of Figure 2.14.

An example of where BDA can be used in this study is when profiling and segmenting the customers' transactional history. The machine running the data mining software automatically searches large databases to identify unexpected correlations in the data (King and Jessen, 2010). Different data mining tools are used for customer profiling and customer segmentation. Unsupervised clustering models are used in the case of customer segmentation, whereas supervised classification models can be used for customer profiling (Tsiptsis and Chorianopoulos, 2009).

Shaw et al. (2001) present a customer profiling system seen in Figure 2.20. This is an example of how data analytics is used for profiling customer information.

In the study by Fan et al. (2015), the authors identify the data mining technique for the marketing mix framework and the application in which it can be used. The marketing mix framework can be found in Section 2.2. Figure 2.21 shows a summary of the data mining techniques identified by Fan et al. (2015) for different applications within the marketing mix.

This concludes the section regarding Big Data and BDA. For the purpose of this study, it is essential to understand the basic principles of different machine learning tools and techniques. The specific techniques to be used will be explained in greater detail later in the study. The following section will discuss the data privacy which may concern customers. The section focuses on security techniques that can be introduced alongside current data mining techniques for data privacy.

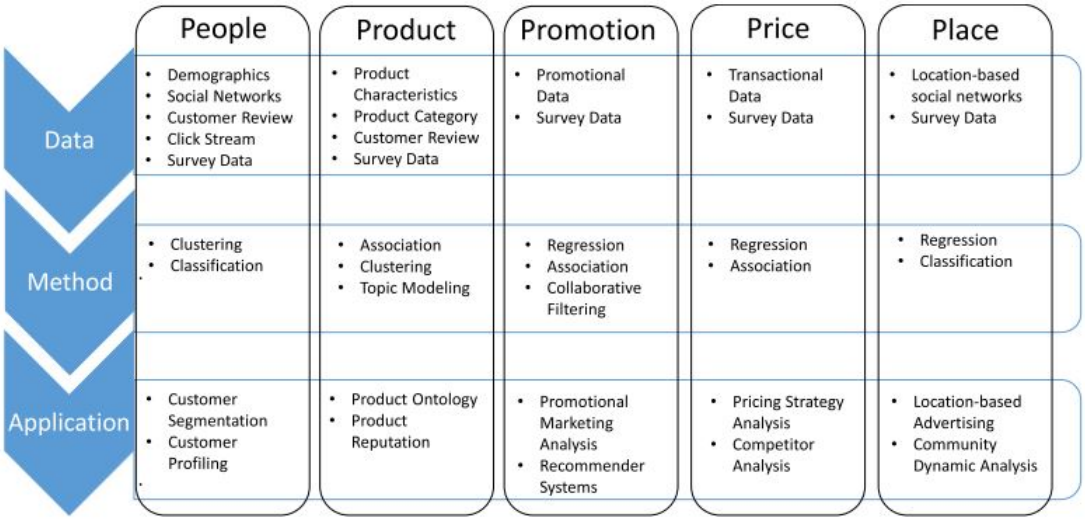


Figure 2.21: Data mining for the mix marketing framework (Fan et al., 2015).

2.9 Data security and privacy

This section touches on the concerns customers may have regarding the privacy of their data when it is used for targeted marking. Customer data are used for the purpose of targeted marketing as mentioned in Section 2.2.

A study conducted by King and Jessen (2010) identifies two main privacy concerns consumers may have regarding targeted marketing. The first is the interference with personal data protection and the second concern is the interference with personal autonomy and liberty. Mobile users communicate large amounts of data which are stored in databases. This may include geographical data, personal identifiable data and behavioural data. The data can be stored as personally-identifying or anonymous.

The concerns with personal data privacy interferences from the study by King and Jessen (2010) can be summarised as:

1. interference with customers' right to personal data protection,
2. pervasive and non-transparent commercial observation of customer behaviour,
3. increased generation of unwanted commercial solicitations,
4. data security concerns,
5. and an increased exposure to potential types of unfair commercial practices.

The interference with privacy is when a customer does not give consent to be tracked by the mobile location. It is also considered an interference when a customer does not receive any notice or give consent for their data to be used in marketing campaigns.

The concern regarding personal autonomy and liberty is when the customer is unaware that personal information is used for targeted marketing purposes. This can lead to customers not being able to exercise their personal autonomy because they are unaware of the profiles created and used for marketing. This again can be rectified by gaining customers access to the profile based on their information after receiving their consent to use the personal information in the first place (King and Jessen, 2010). Information regarding European Union and United States of America regulatory frameworks for targeted advertising can also be found in the study conducted by King and Jessen (2010).

The concerns grow relating to data mining and creating customer profiles. Wu et al. (2014) conducted a study about data mining in Big Data. Within this study, Wu et al. (2014) mentioned that data privacy is one of the important issues within certain domain applications. Simple data transmissions, for example peoples' locations, do not create concern, but can create serious privacy concerns if a customer's location is freely available over a certain time period. Another concern is domain and application knowledge. An example to explain this concern is used with the definition of privacy preservation.

There exist two common approaches to protect the privacy of customer data. The one approach is the simplest one which is restricting the data. This means adding access control on data entries so only certain individuals are granted access to it. A common challenge with this is inventing secured certification or mechanisms for access control (Wu et al., 2014).

The second approach and mostly used is anonymising data fields to ensure that sensitive information cannot be revealed. The objective of this approach is to introduce variation into the collected data in order to ensure a certain number of privacy goals. In response to privacy protection, privacy-preserving data mining is used (Kamber et al., 2012; Fung et al., 2010; Wu et al., 2014).

Dalenius (Fung et al., 2010) defines privacy preservation as: "access to the published data should not enable the adversary to learn anything extra about any target victim compared to no access to the database, even with the presence of any adversary's background knowledge obtained from other sources." An example of this is when the adversary knows Customer X has an age Y years older than the average of an African woman and has access to statistical information about the average age of African women, then Customer X's privacy is compromised.

According to Fung et al. (2010), the data holder has a data table

D(Explicit_ Identifier, Quasi_ Identifier, Sensitive_ Attributes, Non-Sensitive_Attributes),

as the most basic form of Privacy Preserving Data Publishing (PPDP).
Explicit_Identifier is an attribute like *name* which explicitly identifies individuals.

Table 2.22: Anonymisation methods

Method	Description
Generalisation	Transformation rules that allow to iteratively generalise values on an attribute.
Suppression	A specialisation of generalisation where data items are suppressed.
Perturbation	Original data values are replaced with synthetic data values.
Permutation	De-associates the relationship between a quasi-identifier between and the numerical sensitive attribute.

Quasi_Identifiers are attributes that can identify the record owner. *Sensitive_Attributes* refer to the sensitive information of the individuals. *Non-Sensitive_Attributes* are all the other data items not fitted into the three previously mentioned categories.

Anonymisation is the PPDP approach that ensures the privacy of sensitive data or the identity of the record owner such that sensitive data can be maintained for data analysis (Fung et al., 2010). Different methods for anonymisation are available in literature. Table 2.22 provides a summarised description of such methods.

The privacy goals or criteria mentioned earlier, are different kinds of privacy models. The best known is the k-anonymity where each individual must be indistinguishable from the other k-1 individuals. Other types of privacy criteria available are ℓ-diversity, t-closeness and δ-presence (Kohlmayer et al., 2014; Fung et al., 2010).

The reader is referred to Fung et al. (2010) for in-depth knowledge regarding anonymisation algorithms as well as privacy-preserving case studies for classification and clustering analysis. This source also includes anonymisation for transactional data which will be useful in this study.

Research in the field of privacy and more specifically in data mining is a growing field and new approaches are continuously investigated. The next section provides an overview of system architecture in order to implement the model proposed by this study.

2.10 System architecture

In this section an overview is given with the focus on system architecture and its importance in the context of this study. Dori (2002) considered different definitions available in literature before the author proposed the simple but comprehensive definition for a system: "A *system* is an object that carries out or supports a significant function." This definition applies to both artificial and natural systems.

Systems consist of objects, where objects have a potential of existence. If a subset of these objects are capable of doing something it is said to function in a certain way. A *function* is

defined by Dori (2002) as: "An attribute of an object that describes the rationale behind its existence, the intent for which it was built, the purpose for which it exists, the goal it serves, or the set of phenomena or behaviours it exhibits." All systems are objects, but it is based on the function to determine if an object is a system. This is explained via examples that are presented in Dori (2002).

The universe consists of both natural and artificial systems. The difference between these two systems comes in where natural systems are not associated with a premeditated goal or purpose that the function of an artificial system exhibits. The goal of a system is the human's intention of what the system is supposed to do. The function which a system possesses translates this goal to a practical outcome (Dori, 2002). As time passes artificial systems become more complex and revolutionary. With this, the fundamental reason for artificial systems stays the same: to improve the lives of humans.

According to Dori (2002), *system architecture* is the overall system's structure-behaviour combination, which enables it to attain its function while embodying the architect's concept. The concept of a system is the strategies the system architect uses for the system's architecture. The architecture of a system is a vital part in creating a new system in order to understand the structure and behaviour of the system and designing it in such a way that it will achieve the desired goal. This is especially so in the world of today, where diverse and complex innovations are created.

It is important to understand the difference between the function of a system and its the dynamics. The function of a system answers the '*what* the system does' and '*why* the system does it' type of questions. Contrary to this, the dynamics of a system refer to the question of '*how* the system does it'. Thus, the dynamics of the system refer to the behaviour and how the system acts to attain the function.

The function of a system can be better understood by considering the system as having two parts: the structure and the behaviour. The structure refers to the entirety of the system and the relationship between components which do not change over time. Behaviour is dynamic and changes as time passes. These changes are obtained within one or more subsystems that are incorporated in the system.

Dori (2002) states that it is impossible to separate the structure and the behaviour of a system because the dynamics determine what happens to the system. In some scenarios the combination of structure and behaviour is needed for the system to function and attain the specified goal.

In order to design a system capable of analysing Big Data, Chen and Zhang (2014) summarised seven crucial principles to keep in mind. The principles are:

1. Good architectures and frameworks are necessary and on the top priority.

2. Support a variety of analytical methods.

3. No size fits all.
4. Bring the analysis to data.
5. Processing must be distributable for in-memory computation.
6. Data storage must be distributable for in-memory storage.
7. Coordination is needed between processing and data units.

It is important to acknowledge the basic principle of systems for the purpose of this study, as well as the importance of a well-defined system architecture in order to design a system with the correct structure and dynamics to achieve the particular goal. The following section will synthesise the knowledge gained up to this point in order to create perspective within the goals of this study.

2.11 Literature synthesis

CRM explains in broad perspective the management of the relationship of an enterprise with its customers and the importance of this. One of the activities to retain customers is to providing them with cross-selling and upselling opportunities to increase their customer experience. Cross-selling and upselling are methods used to retain customers and aim at bettering targeted marketing based on customer product usage. It is for this reason that marketing is of importance since it places the focus on the communication between the enterprise and its customers. Various marketing strategies are available and personalised marketing strategies are necessary if individual customers are targeted. Where marketing strategies focus on communication with the customer, pricing strategies and special offers focus on what is being communicated. Pricing strategies include promotional pricing which is used to define what is offered to the customer and the cost implications to the enterprise. Pricing strategies are used when offering cross-sell or upsell products.

In order to create personalised cross-selling and upselling offers, the customer must be known and this is the point where customer profiles are of importance. Customer profiles describe the customers in a factual and behavioural manner. Knowledge can be discovered within the data of customers by analysing the customer profiles, where after enterprises can identify the needs of their customers more accurately. Analytics are tools and techniques needed to analyse the data and various options are available. Big Data Analytics are also available to be applied to datasets defined as Big Data. When the behaviour of the customer is known the appropriate marketing strategy and pricing strategy can be applied to ensure customer satisfaction when attempting to create cross-sell and upsell offers to retain customers.

The concept of analysing customer data creates the opportunity for data security risk and it is for this reason that when analysing customer data, data security and privacy must be fully understood and implemented. In creating a system which incorporates some of these knowledge areas a system architecture is necessary. It is important to gain the required theoretical knowledge regarding system architectures in order to utilise it.

2.12 Chapter 2 summary

In this chapter, elements of the literature required to understand the different knowledge areas included in this study were described. CRM, marketing and pricing strategies, cross-selling and upselling and customer profiles were discussed to better understand each topic and their relationship with each other. Knowledge discovery, Big Data and Big Data Analytics were investigated as these are included in the technical development of the study. A literature synthesis was also provided to fully understand the purpose of each knowledge area discussed in the study, where they are related and the relationship between them. The literature provided about system architecture is applied to develop an architecture for the proposed system of this study. This will be the topic of discussion in the next chapter.

Chapter 3

System architecture

At the end of the previous chapter, system architecture was broadly explained. In this chapter the researcher presents more detail regarding the methodology followed for the system architecture in this study. Furthermore, the researcher constructed an architecture for the desired system which is also presented in this chapter.

The researcher must identify an appropriate methodology to be utilised in the construction of the system architecture of the proposed system. Thereafter, the researcher will use the identified methodology to create the architecture and explain the relevance of each part within the process. The researcher must also visualise the proposed model with the different parts.

3.1 Object-Process Methodology

In order to construct a system architecture, it is important to identify and understand the methodology that is necessary to do this. *Object-Process Methodology* (OPM) is an intuitive methodology that models the complexity of systems in a coherent way. Development and support is needed throughout the life cycle of artificial models. This calls for a comprehensive methodology that includes all challenging points in the evolution of a system (Dori, 2002).

As mentioned in Section 2.10, system models consist of three main aspects which are the *function*, the *structure* and the *behaviour* of the system. These aspects are alike for both artificial and natural systems, which makes OPM an unambiguous approach to gain a holistic view of a system. OPM is an ISO certified methodology (ISO 19450) which declares that it is sufficient for practitioners to use OPM as a modelling paradigm to conceptualise systems in varying amounts of detail.

Alongside the holistic view OPM provides, it also includes a textual counterpart. *Object-Process Language* (OPL), which is an automatically generated description of the desired system, is a description extracted from the visual description of the diagram and provided in a subset of natural English (Dori, 2002). According to Dori (2002), OPL has two goals. One is to convert the Object-Process Diagram (OPD) into a natural language that can be understood by users. This also includes stakeholders with low-level programming knowledge. The second goal is to present an infrastructure for further application development. The value of using OPM is in the visual graphics and semantics which make it easy to understand.

The researcher will follow the OPM to design the system architecture for the proposed model. Designing an architecture for the desired system is crucial in order to understand the interconnection between different processes and to gain an overall view of the desired system. The architecture design ensures that the researcher addresses the problem set by the problem

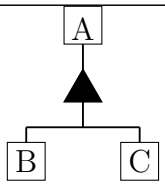
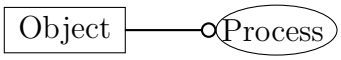
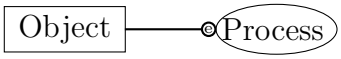
statement provided in Chapter 1. The following section provides the OPDs for the proposed model of this study along with the OPL.

3.2 Personalised Discount Offer architecture

This section contains the OPDs of the proposed system. This is of value for the researcher because it provides a holistic view of the system and its intended function. In OPM three entities exist: *objects*, *processes* and *states*. Objects exist and can be transformed by processes. This is done by generating, consuming or affecting the objects. States are used to describe objects and cannot be used alone. Objects can be at some state at any point of time in the system (Dori, 2002).

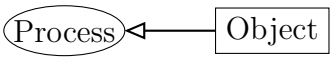
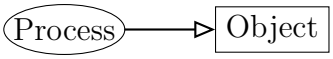
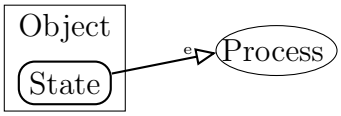
The blue *ellipse* symbols in the diagram represent the processes of the desired system. The system is composed of a variety of processes working together. The green *rectangles* represent the objects in the system. Objects can either have a solid frame or a dashed frame. Objects with a dashed frame cannot be changed by the system itself. Solid frame objects are transformed by the processes in the system and subsystems. The names of the processes or objects are each given a corresponding symbol. The links used to connect the processes and objects are presented in Table 3.1.

Table 3.1: OPM legend (Dori, 2002).

Link Name	**OPD Symbol**	**OPL Sentence**	**Description**
Aggregation-Participation		**Object A** consists of **Object B** and **Object C**.	The relation between a whole and its parts.
Instrument		**Processing** requires **Object**.	Process needs the instrument object in order to occur. Object is not changed by the process.
State-specified instrument		**Object** triggers **Processing** when it enters **State**.	The object in the specified state both triggers the process and is instrumental for its execution.

Continued on next page

Table 3.1 continued

Link Name	OPD Symbol	OPL Sentence	Description
Consumption		**Processing** consumes **Object**.	Process uses object up entirely during its occurrence.
Result		**Processing** yields **Object**.	Process creates an entirely new object during its occurrence.
State-specified consumption		**Object** triggers **Processing** when it enters **State**.	The object in the specified state both triggers the process and is consumed by it.

The top-level system diagram of the proposed model can be viewed in Figure 3.1. This system diagram includes two processes: *Personalised Discount Offer* (PDO) *Identifying* and *Customer Acquisitioning*. The PDO Identifying process uses the *Data Analytics*, *Customer Profile* and *Retailers* to identify appropriate *Discount Offers* for customers. The Customer Profile consists of different objects, namely: *Customer Handle*, *Preferences*, *Transactional History* and *Customer Location*. These objects are all needed to create a distinguishable customer profile for a specific customer. The Retailers consist of *Branches*. The Branches consist of the *Outlet Layout*, *Products* and *Outlet Location*. This information distinguishes each store in the same retailer group, because each branch has a unique location.

The second process in Figure 3.1 represents the Customer Acquisitioning process. This process needs the Customer Location and the Outlet Location and uses the Discount Offers created by the PDO Identifying process. The Customer Acquisitioning process yields a Transactional History, which creates a feedback loop to update the Customer Profile that ensures appropriate Discount Offers are identified in return. The Customer Acquisitioning process is a subsystem within the top-level system. The OPL of Figure 3.1 is given as follows:

Data Analytics is environmental.
Customer Profile consists of Customer Handle, Preferences, Transactional History, and Customer Location.
    Customer Handle is environmental.
    Preferences is environmental.
Retailers is environmental.
Retailers consists of Branches.
    Branches is environmental.
    Branches consists of Outlet Layout, Products, and Outlet Location.
        Outlet Layout is environmental.

Outlet Location is environmental.
PDO Identifying requires Retailers, Customer Profile, and Data Analytics.
PDO Identifying yields Discount Offers.
Customer Acquisitioning is physical.
Customer Acquisitioning requires Customer Location and Outlet Location.
Customer Acquisitioning consumes Discount Offers.
Customer Acquisitioning yields Transactional History.

The top-level process Customer Acquisitioning is zoomed in for more detail in Figure 3.2. The lower-level processes within Customer Acquisitioning are *Discount Offer Processing*, *Discount Offer Noticing*, *Customer Decision Recording* and *Checkout Processing*. The top-level process also exhibits objects, namely, *Offer Applicable, Discount Offer Notification Received* and *Recorded Customer Decision*.

The Discount Offer Processing process requires the Outlet Location and the Customer Location and consumes the Discount Offers produced by the top-level process, PDO Identifying. These objects are displayed on the zoomed-in system diagram because they are used in the lower-level process. The Discount Offer Processing process assesses whether the specific customer will be susceptible to a PDO and whether it must be offered. The process yields an object, Offer Applicable, which can be in a state of *Yes* or *No*. If the object is in the state of No, the customer is not presented with a PDO and it triggers the normal Checkout Processing process.

If the Offer Applicable enters the state of Yes, it triggers the Discount Offer Noticing process. This process sends a PDO to the specific customer via their mobile device. The object, Discount Offer Notification Received, represents the instance where the customer receives the PDO on their mobile device. This is followed by a process, Recorded Customer Decision, where the customer's decision to accept or reject the PDO is recorded. After recording the customer's decision, the process Checkout Processing, is triggered. The Checkout Processing process develops into another lower-level subsystem and is the focus of Figure 3.3.

The Checkout Processing process yields the Transactional History, which in return is the feedback loop to the top-level OPD. The OPL of Figure 3.2 is produced by the OPM as follows:

Outlet Location is environmental.
Customer Acquisitioning is physical.
Customer Acquisitioning exhibits Offer applicable, Discount Offer Notification Received, and Recorded Customer Decision.
Customer Acquisitioning consists of Discount Offer Processing, Discount Offer Noticing, Customer Decision Recording, and Checkout Processing.

Customer Acquisitioning zooms into Discount Offer Processing, Discount Offer Noticing, Customer Decision Recording, and Checkout Processing, as well as Recorded Customer Decision, Discount Offer Notification Received, and Offer applicable.

Recorded Customer Decision triggers Checkout Processing.
Discount Offer Notification Received is physical.
Offer Applicable can be No or Yes.
Offer Applicable triggers Checkout Processing when it enters No.
Offer Applicable triggers Discount Offer Noticing when it enters Yes.
Discount Offer Processing requires Outlet Location and Customer Location.
Discount Offer Processing consumes Discount Offers.
Discount Offer Processing yields Offer Applicable.
Discount Offer Noticing requires Yes Offer Applicable.
Discount Offer Noticing yields Discount Offer Notification Received.
Customer Decision Recording requires Discount Offer Notification Received.
Customer Decision Recording yields Recorded Customer Decision.
Checkout Processing is physical.
Checkout Processing consumes No Offer Applicable and Recorded Customer Decision.
Checkout Processing yields Transactional History.

The lower-level process, Checkout Processing, is zoomed in to show another subsystem. This system diagram can be seen in Figure 3.3. This process consists of three lower-level processes: *Products and App Scanning, Customer Decision Application Process* and *Updating Transactional History*. The objects, Offer Applicable and Record Customer Decision are produced in the Customer Acquisitioning process and used in the Checkout Processing process. The object Transactional History is used in the top-level system diagram, but is yielded by the process Updating Transaction History. The Products and App Scanning process represents the point of sale where the products and the PDO Application on the customer's mobile device are scanned. This process yields an object, *Purchased Item List*, which represents the list of products the customer bought.

If the Offer Applicable object went into the Yes state, a Recorded Customer Decision object would have been created as seen in Figure 3.2. In this case, the Customer Decision Application Process is triggered by the Recorded Customer Decision object and consumed along with the Purchased Item List. In this process, the customer's decision is applied in the system. This process happens regardless of the choice the customer made. The process yields an Adapted Purchased Item List. This object includes the discount in the case where the customer accepted the PDO. The Adapted Item List is consumed by the Updating Transaction History.

In the case where the Offer Applicable object went into the No state, the Purchased Item List is consumed by the Updating Transaction History process. These are the instances where

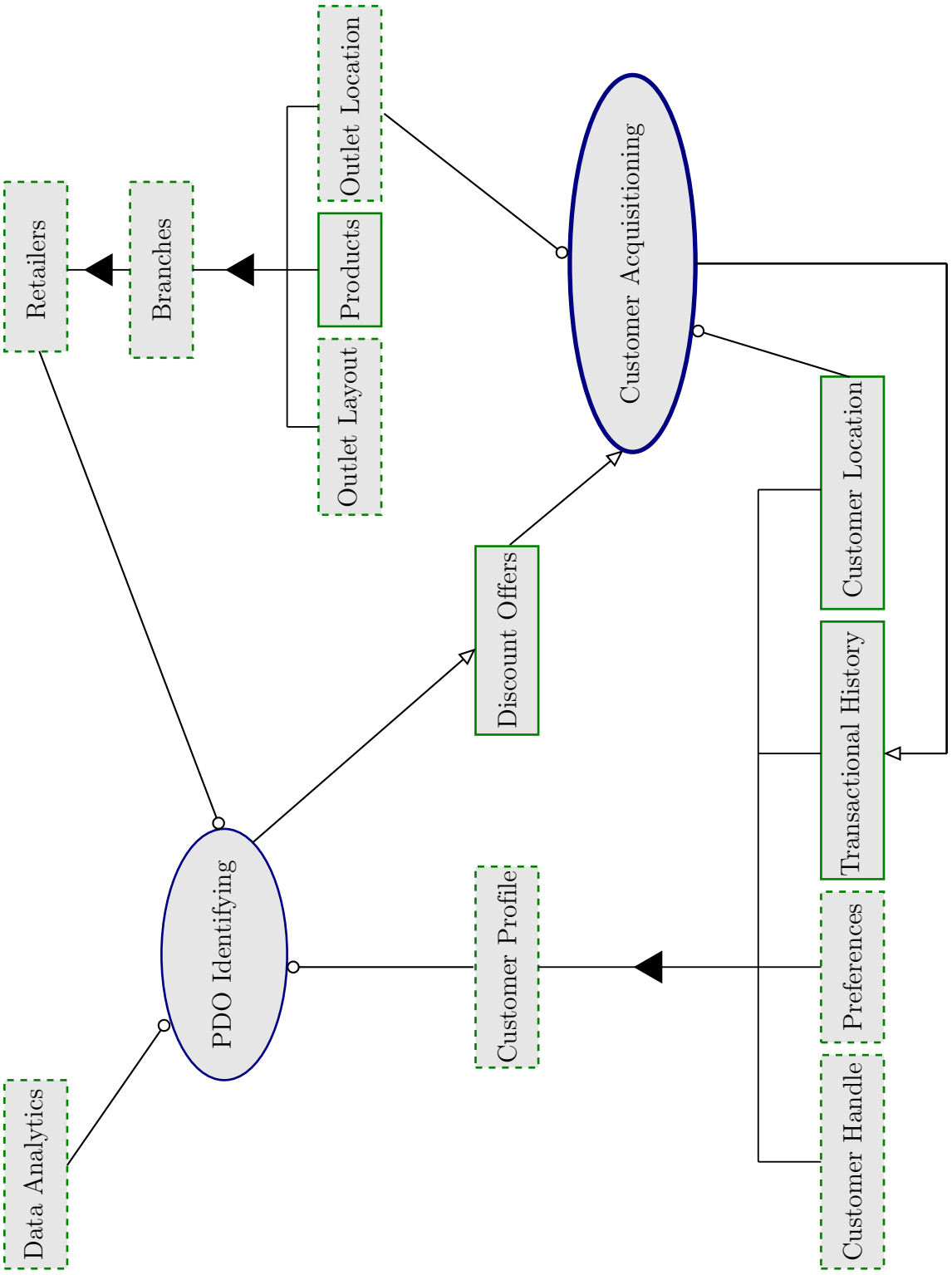


Figure 3.1: Top-level system architecture of proposed demonstrator model for personalised discount offers

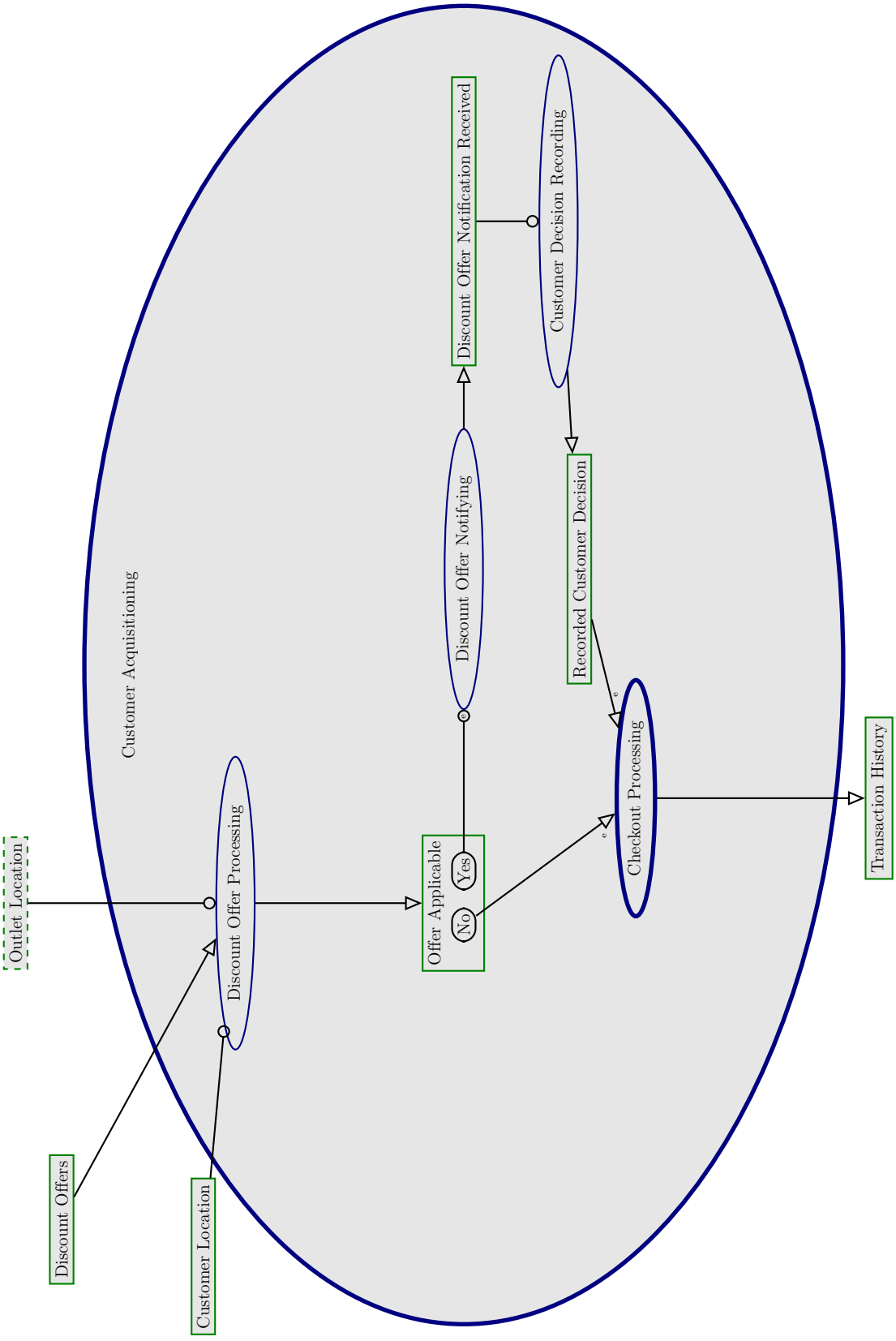


Figure 3.2: Zoomed-in system architecture of the Customer Acquisitioning process from Figure 3.1

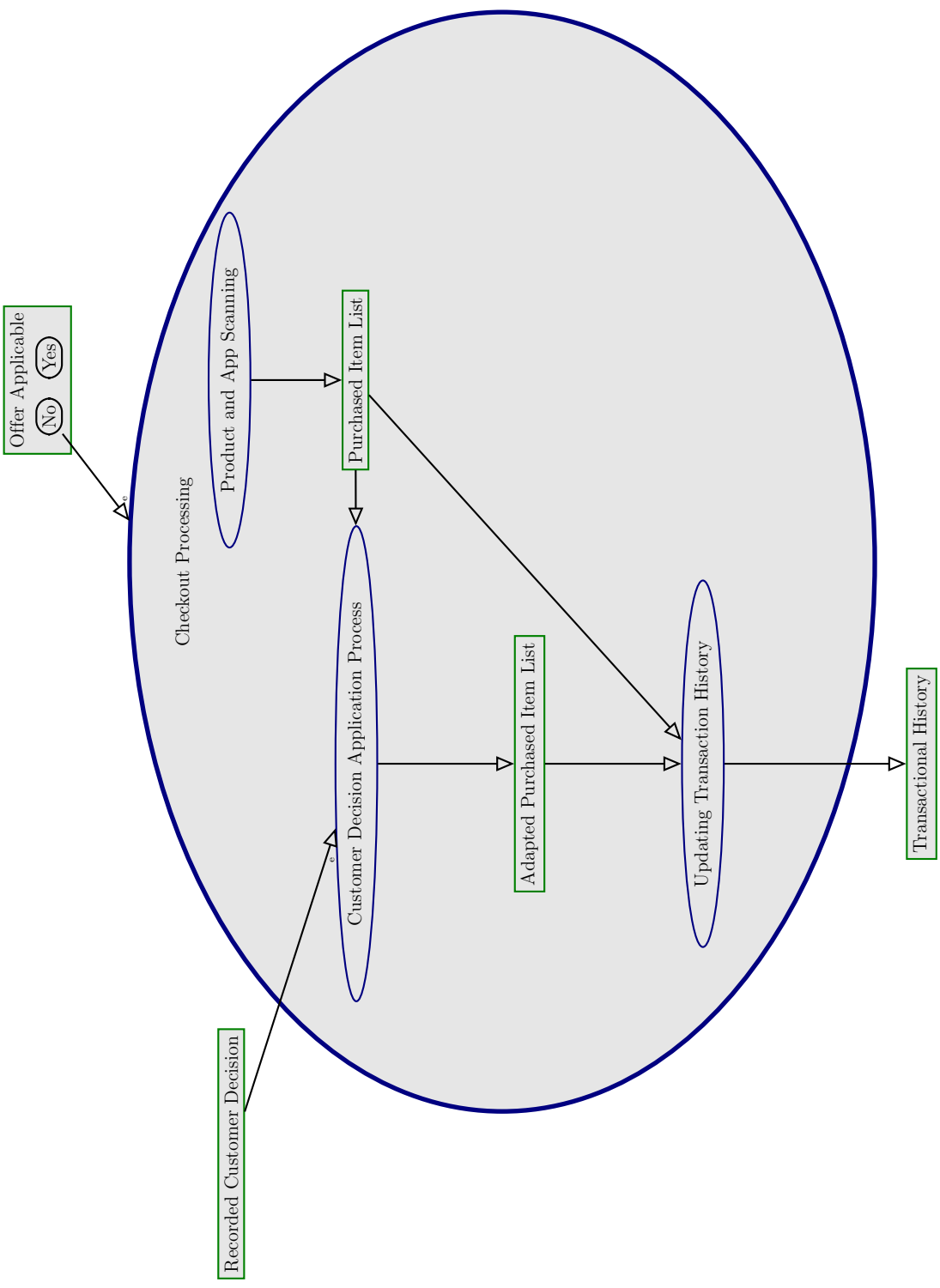


Figure 3.3: Zoomed-in system architecture of the Checkout Processing process from Figure 3.2

customers did not receive any PDOs. The Updating Transaction History updates and yields the Transactional History of the specific customer. The Transactional History is an object in the top-level system diagram and is the feedback loop that in return is used as part of the Customer Profile. The system is also updated with the customer's decision to accept or reject the PDO. The OPL of the Checkout Processing process is given as,

Offer Applicable can be No or Yes.
Offer Applicable triggers Checkout Processing when it enters No.
Recorded Customer Decision triggers Customer Decision Application Process.
Checkout Processing is physical.
Checkout Processing exhibits Purchased Item List and Adapted Purchased Item List.
Checkout Processing consists of Products and App Scanning, Customer Decision Application Process, and Updating Transaction History.
Checkout Processing consumes No Offer Applicable.
Checkout Processing zooms into Products and App Scanning, Customer Decision Application Process, and Updating Transaction History, as well as Adapted Purchased Item List and Purchased Item List.
Products and App Scanning is physical.
Products and App Scanning yields Purchased Item List.
Customer Decision Application Process consumes Purchased Item List and Recorded Customer Decision.
Customer Decision Application Process yields Adapted Purchased Item List.
Updating Transaction History consumes Adapted Purchased Item List and Purchased Item List.
Updating Transaction History yields Transactional History.

3.3 Schematic view of the proposed system

The previous section explained the system architecture of the proposed system. This section will provide a schematic overview of the proposed system, which will be presented as a demonstrator model and the different parts and their functionalities. The proposed system is referred to as a demonstrator since the implementation thereof is beyond the scope of this study.

The researcher decided to use simulated data in the proposed model in order to overcome ethical issues. The model requires the data to be in a very specific format and this is another contributing reason why the researcher decided to use simulated data. The PDO demonstrator requires a simulator, which simulates all the necessary data and a *PDO predictor*, which provides PDOs to customers. These two subsystems will be distinctly referred to from this point onwards. Figure 3.4 visualises the relationship and difference in functionality between

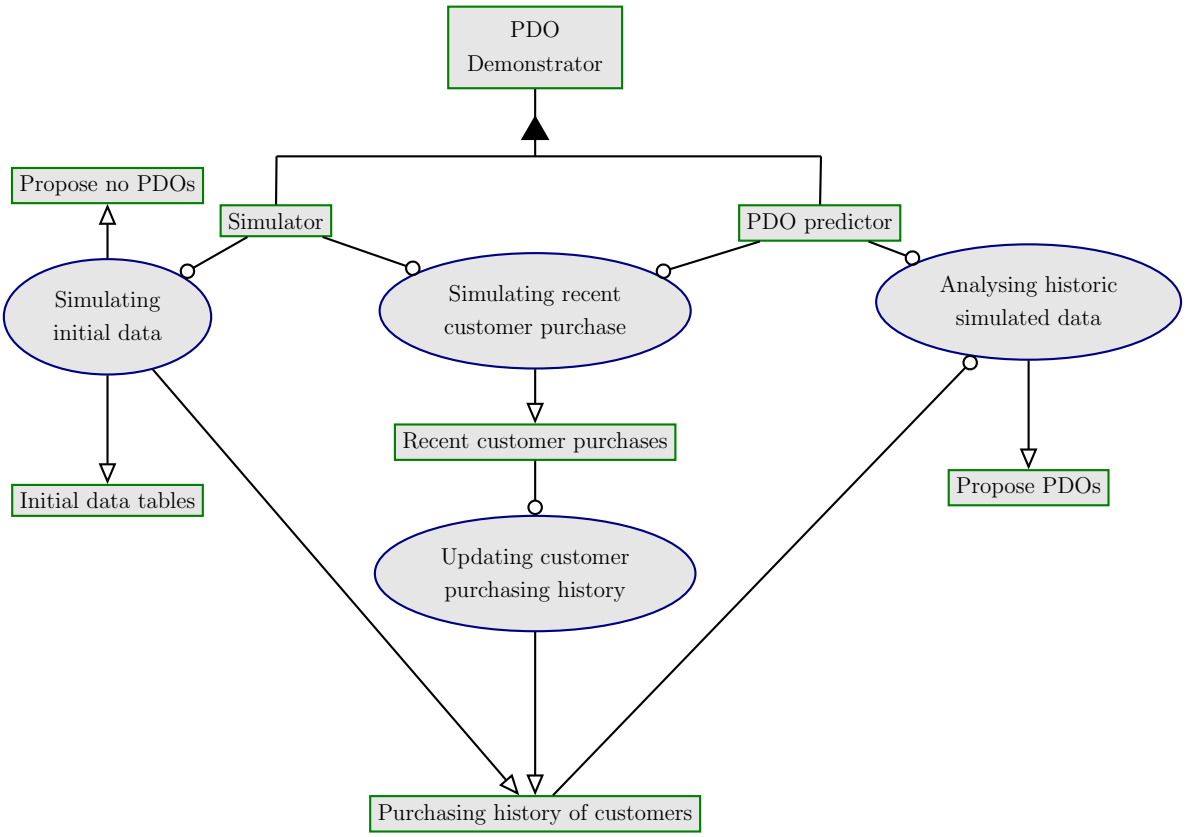


Figure 3.4: Schematic view of the proposed demonstrator model

the simulator and the PDO predictor that together presents the PDO demonstrator model.

The simulator creates initial data tables and initial historic data of customers without any PDO analysis. This is only done once at the beginning of the simulation, hereafter the PDO demonstrator is used. The PDO demonstrator requires a partial functionality of the simulator in order to continue creating customer purchases, but also emulate the real world process as PDOs are identified by the PDO predictor and offered from this point onwards.

3.4 Chapter 3 summary

In this chapter the researcher explained why OPM is an appropriate methodology for the system architecture of the proposed model in this study. The importance of system architectures is also discussed. The researcher constructed system diagrams, using the OPM. An explanation of the different processes and objects is given along with the OPL that is created by the OPM. Lastly, the researcher explained the necessity for the simulator in the study and the relationship and difference between the simulator, PDO predictor and the PDO demonstrator. Chapter 4 is focused on the design and development of the simulator that will be used to create a transactional history for the PDO demonstrator model in this study.

Chapter 4

Design and development of the simulator

The previous chapter informed the reader about the system architecture of the proposed model. This chapter encompasses the design and development of the simulator. The simulator is used to create initial pseudo-customer data containing personal information and purchasing behaviour. The methodology followed for the design and development of the simulator will initiate this chapter.

4.1 Simulator design and development methodology

This chapter represents the start of phase two of the research methodology explained in Section 1.5. The researcher will start the design of the simulator by identifying the functionalities needed within the simulator. During this part the researcher must identify the entities needed in the system as well as the entity-relationships that exist between them. This will be realised by using an *Extended Entity–Relationship Diagram* (EERD). In order to create these entities, a data dictionary is needed to describe the attributes of each entity. After the design of the simulator the researcher must develop the simulator and for this a database will be needed. The researcher must identify the database to be used as well as the program to be used for the development of the simulator. The researcher must explain how the entities are populated during the development of the simulator.

4.2 Design of the simulator

The design of the simulator commenced based on the system architecture using Object Process Methodology (OPM) as described in Chapter 3. The goal of the simulator can be divided into two parts or functionalities. It is initially used to populate empty data tables so that data is available for analysis. Then it is used to create an initial customer purchasing history and thereafter the continued simulation of the customer purchasing history. A summary of this can be seen in Figure 4.1. The functionality of the continued customer purchasing history simulation will be used within the PDO demonstrator which is the subject of discussion in Chapter 5.

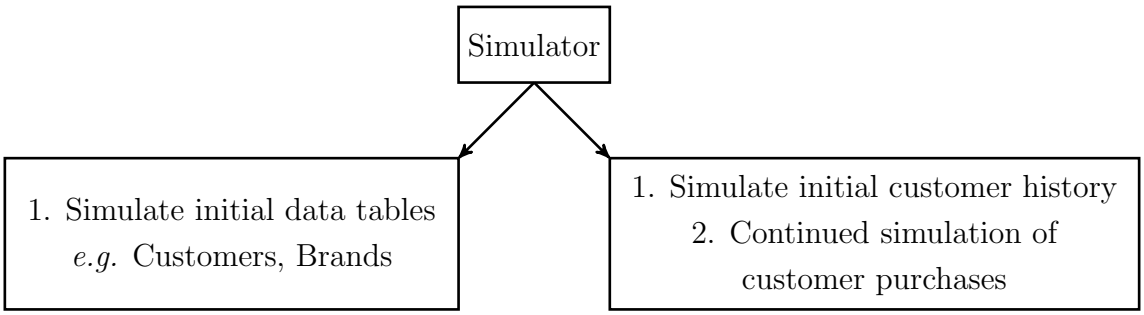


Figure 4.1: Schematic view of simulator functionalities

4.2.1 Entities

It is clear from Figure 3.1 that information regarding customers, outlets and products is needed. An entity may represent people, places, things and events (Kendall and Kendall, 2014). Thus, the first entities to be created are the *primary entities*. These entities represent the initial data that are used in the simulator to create and update the purchasing history. The entities contain original attributes and do not contain information from other entities. These entities present finite lists with information regarding each entity. The primary entities identified to be created by the simulator are *Customers*, *Retailers*, *Branches*, *Product Categories*, *Personalised Discount Offers Types* and *Preferences*.

After deciding on the primary entities, it became clear which *attributive entities* were needed. The attributive entities are different from the primary entities as they contain information from the primary entities along with their individual information. The attributive entities in the simulator are *Orders*, *Products*, *Outlets*, *Transactional History* and *Personalised Discount Offers* (PDO).

The last type of entities created by the simulator are the *associative entities*. These entities contain information from the other two types of entities and are used to join entities. The associative entities that must be created by the simulator are *Customers_Preferences*, *Outlets_Products*, *Personalised Discount Offers Accepted*, *Personalised Discount Offers Rejected* and *Personalised Discount Offers Origin*. The following section explains the relationship between entities.

Each entity contains characteristics of the entity and are called *attributes* according to Kendall and Kendall (2014). Attributes are the smallest units in a file or database. A record is a collection of attributes that have something in common with the entity. In the case of the simulator data structure, each table entry would be a record. The relationship between entities is discussed in the following subsection.

4.2.2 Entity–Relationship

Identifying the entities is the starting point to designing the simulator. The relationship between entities is very important to understand as they represent the association between entities. The crow's foot notation is used to describe the relationships between entities (Kendall and Kendall, 2014). Each symbol in the EERD has a different meaning. The meaning of each symbol is summarised in Table 4.1. Table 4.2 illustrates the different types of relationships that can be found between entities.

Table 4.1: Illustrating the symbols and meanings of the Extended Entity–Relationship diagram, adapted from Kendall and Kendall (2014).

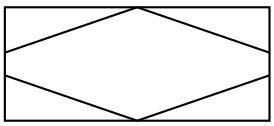
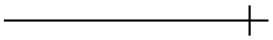
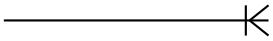
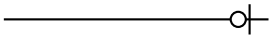
Symbol	Official explanation	What it means
	Primary Entity	A class of persons, places, things or events.
	Attributive Entity	Used for repeating groups.
	Associative Entity	Used to join two entities.
	To 1 relationship	Exactly one.
	To many relationship	One or more.
	To 0 or 1 relationship	Only zero or one.

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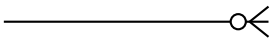
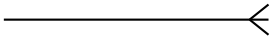
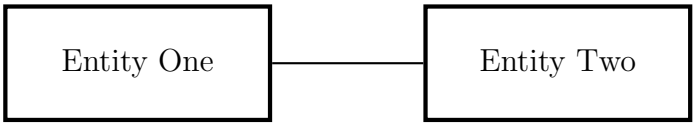
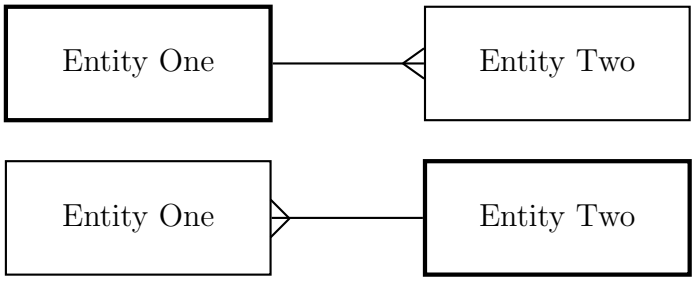
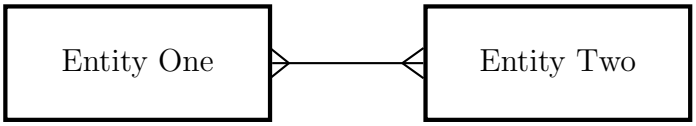
Table 4.1 continued		
Symbol	**Official explanation**	**What it means**
	To 0 or more relationship	Can be zero, one, or more.
	To more than 1 relationship	Greater than one.

Table 4.2: Illustrating the different relationships of the Extended Entity–Relationship diagram, adapted from Kendall and Kendall (2014).

Example of E – R Diagram	**Relationship**
	One-to-one (1:1)
	One-to-many (1:M) or Many-to-one (M:1)
	Many-to-many (M:N)

An EERD is developed to illustrate the relationship between the entities that were identified in Subsection 4.2.1. The EERD for the simulator can be observed in Figure 4.2.

As mentioned in Subsection 4.2.1 entities contain attributes. A *primary key* (PK) is an attribute of an entity that is used to uniquely identify a record. Thus, the primary entities and

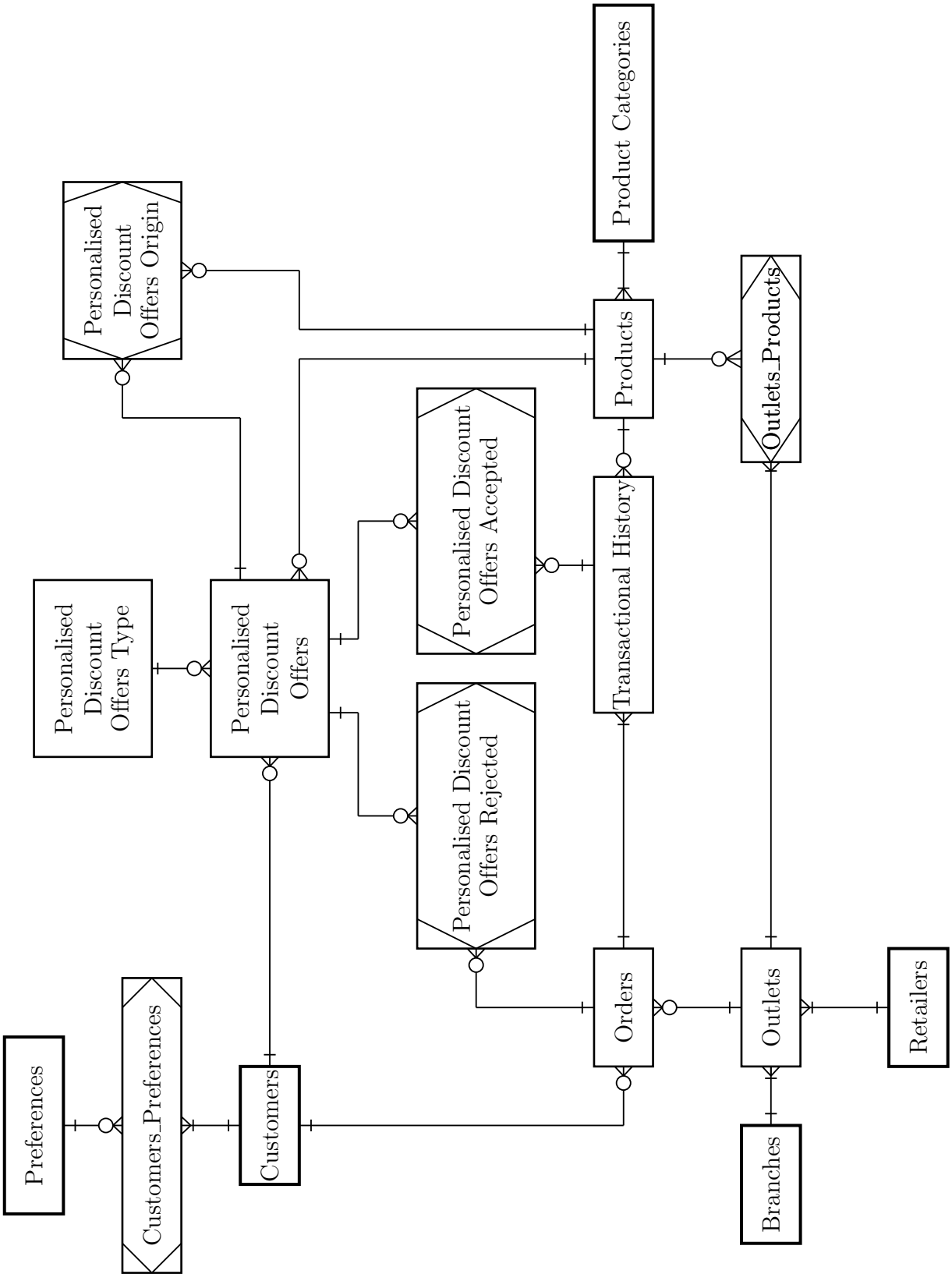


Figure 4.2: Extended Entity-Relationship diagram of the simulator

the attributive entities have PKs. However, the associative entities do not contain a primary key, but rather the unique combination of the primary keys from the joining entities. This is called a *composite key* or *compound key* (Kendall and Kendall, 2014).

Foreign keys (FK) are used when referring to attributes that are primary keys in other entities (Kendall and Kendall, 2014). Attributive entities and associative entities both contain foreign keys referring to records in other entities. The attributes for each of the entities identified in Subsection 4.2.1 are assigned in the following subsection.

4.2.3 Data dictionary

The EERD in Figure 4.2 illustrates the relationship between the entities that were defined for the simulator. A *data dictionary* (DD) is a reference work of data about data, thus contains metadata. A DD is created for the simulator to collect and coordinate different data terms and ensure the data are consistent (Kendall and Kendall, 2014). The data dictionary is used when tables are created in the database. Each entity contains a number of attributes. The attributes, their data types and a description of the attribute are given in the data dictionary. The DD of the primary entities of the simulator is described in Table 4.3 to Table 4.8. The first entity to follow is `Customers`.

Table 4.3: Customers table data dictionary

Attribute	Data Type	Description
CustID	bigint	PK – Unique key to identify this customer.
CustHandle	varchar	This is the handle a customer use to register to the service.
LastPurchase	varchar	The last date a customer made a purchase.

The primary entity `Retailers`, represents the different retail outlets that participate in the service. The data dictionary of this entity can be seen in Table 4.4.

Table 4.4: Retailers table data dictionary

Attribute	Data Type	Description
RetailerID	bigint	PK – Unique key to identify this retailer.
RetailerName	varchar	This is the name of a retailer participating in this service.

Branches refers to the participating outlets of the different participating Retailers as mentioned before. The data dictionary of this entity can be seen in Table 4.5.

Table 4.5: Branches table data dictionary

Attribute	Data Type	Description
BranchID	bigint	PK – Unique key to identify this branch.
BranchName	varchar	This is the name of a branch that forms part of a retailer participating in this service.

The `Preferences` entity refers to different preferences a customer can select when signing up for the service. The various preference attributes are shown in Table 4.6.

Table 4.6: Preferences table data dictionary

Attribute	Data Type	Description
PrefID	bigint	PK – Unique key to identify this preference category.
PrefCat	varchar	This is the name of a preference category a customer can choose from.

The `Product Categories` entity refers to a variety of categories into which products can be sorted. The different product category attributes are shown in Table 4.7.

Table 4.7: Product Categories table data dictionary

Attribute	Data Type	Description
PCID	bigint	PK – Unique key to identify this product category.
CatName	varchar	This is the name of a product category a product are linked to.

The `Personalised Discount Offer Types` entity refers to the different types of personalised discount offers that a customer can receive. The attributes are shown in Table 4.8.

Table 4.8: Personalised Discount Offer Types table data dictionary

Attribute	Data Type	Description
PDOTypeID	bigint	PK – Unique key to identify this personalised discount offer type.
PDOTypeName	varchar	This is the name of a personalised discount offer type.

Table 4.9 to Table 4.13 represent the attributive entities of the simulator. The different products contained in this service are represented by the `Products` entity. The data dictionary for the `Products` entity is shown in Table 4.9.

Table 4.9: Products table data dictionary

Attribute	Data Type	Description
ProductID	bigint	PK – Unique key to identify a product.
ProductName	varchar	This is the name of a product that is available at an outlet.
Feature	varchar	This is the feature of a product that is available at an outlet.
UnitPrice	money	The price at which the products are currently sold.
PCID_FK	bigint	FK – This is the unique ID of the Product Category the product belong to.
Size	varchar	This represents the size of the product.

The attributes of the `Outlets` entity are shown in Table 4.10. The `Outlets entity` represents all the stores participating in this service.

Table 4.10: Outlets table data dictionary

Attribute	Data Type	Description
OutletID	bigint	PK – Unique key to identify the outlet.
RetailerID_FK	bigint	FK – This is the unique ID of the retailer the outlet is part of.
BranchID_FK	bigint	FK – This is the unique ID of the branch the outlet is part of.
OutletLocation	varchar	The location of the specific outlet.

The `Orders` entity represents a continuous table that records every purchase a participating customer makes. The data dictionary for the `Orders` entity is provided in Table 4.11.

Table 4.11: Orders table data dictionary

Attribute	Data Type	Description
OrderID	bigint	PK – Unique key to identify the instance a customer makes a purchase.
CustID_FK	bigint	FK – This is the unique ID of the customer that is making a purchase.
Date	varchar	The date on which the customer makes a purchase.
Time	varchar	The time on which the customer makes a purchase.
OutletID_FK	bigint	The outlet at which the customer makes a purchase.

The `Transactional History` entity is also a continuous table that records every product

that is acquired during each purchase a participating customer makes. Table 4.12 shows the data dictionary of the `Transactional History` entity.

Table 4.12: Transactional History table data dictionary

Attribute	Data Type	Description
THID	bigint	PK – Unique key to identify each product the customer acquires at a purchasing instance.
OrderID_FK	bigint	FK – This is the unique ID of the order identifying the instance a purchase is made.
ProductID_FK	bigint	FK – This is the unique ID of the product the customer bought during a purchasing instance.
Quantity	bigint	The quantity of the specific product the customer bought during a purchasing instance.
UnitPrice	money	The price at which the product is sold during a purchasing instance.

The `Personalised Discount Offers` (PDO) entity represents the PDO that is identified and presented to the customer and is also a continuous table. The data dictionary of the PDO entity is provided in Table 4.13.

Table 4.13: Personalised Discount Offers table data dictionary

Attribute	Data Type	Description
PDOID	bigint	PK – Unique key to identify each PDO.
CustID_FK	bigint	FK – This is the unique ID of the customer receiving a PDO.
ProductID_FK	bigint	FK – This is the unique ID of the product the customer received a PDO on.
Discount	real	The amount of discount the PDO offers.
PDOTypeID_FK	bigint	FK – This is the unique ID of the type of PDO that is proposed.
Status	int	The status of whether or not the customer accepts the PDO, cross-sell or up-sell offer.

The associative entities of the model are represented by Table 4.14 to Table 4.18. The `Customers_Preferences` entity is explained in Table 4.14.

Table 4.14: Customers_Preferences table data dictionary

Attribute	Data Type	Description
CustID_FK	bigint	FK – This is the unique ID to identify the specific customer.
PrefID_FK	bigint	FK – This is the unique ID to identify the specific preference for the specific customer.

Table 4.15 shows the data dictionary of the `Outlets_Products` entity.

Table 4.15: Outlets_Products table data dictionary

Attribute	Data Type	Description
OutletID_FK	bigint	FK – This is the unique ID to identify the specific outlet.
ProductID_FK	bigint	FK – This is the unique ID to identify the specific product.
XYLocation	varchar	This identifies the unique location of the specific product in the specific outlet.
SOH	bigint	This states the stock on hand for the specific product in the specific outlet.

The `Personalised Discount Offers Accepted` entity is a continuous table and is shown by the data dictionary in Table 4.16.

Table 4.16: Personalised Discount Offers Accepted table data dictionary

Attribute	Data Type	Description
PDOID_FK	bigint	FK – This is the unique ID to identify the PDO that is identified and presented to a specific customer.
THID_FK	bigint	FK – This is the unique ID to identify the specific product and the purchasing instance a specific customer accepts the PDO.

As with the `Personalised Discount Offers Accepted` entity, the `Personalised Discount Offers Rejected` entity is also a continuous table and is shown by the data dictionary in Table 4.17.

Table 4.17: Personalised Discount Offers Rejected table data dictionary

Attribute	Data Type	Description
PDOID_FK	bigint	FK – This is the unique ID to identify the PDO that is identified and presented to a specific customer.
OrderID_FK	bigint	FK – This is the unique ID to identify the specific instance when a customer rejects a PDO of a specific product.

The last entity identified in the design stage of the simulator is the `Personalised Discount Offers Origin` entity. This is also a continuous table and is shown by the data dictionary in Table 4.18.

Table 4.18: Personalised Discount Offers Origin table data dictionary

Attribute	Data Type	Description
PDOID_FK	bigint	FK – This is the unique ID to identify the specific PDO.
ProductID_FK	bigint	FK – This is the unique ID to identify the specific product a cross-sell or upsell originated from.

The EERD and data dictionary visualise the data structure of the simulator in a holistic manner and through an iterative process the researcher ensured that all necessary aspects are included to develop the simulator. The information in this section is used for the development of the simulator, which is the topic of discussion in the following section.

4.3 Development of the simulator

This section presents the development of the simulator designed in the previous section. The entities identified in the design stage represent the data tables that are created in the database. The tables are created in Microsoft®[1](MS) SQL Server Management Studio®[1]. The tables are linked with each other as represented by the EERD shown in Figure 4.2 to create a database structure in MS SQL Server.

Matlab®[1] is used to populate the tables in the MS SQL Server database. An Open Database Connectivity (ODBC) data connection was created between MS SQL Server and Matlab using the Matlab Database Explorer Application. Figure 4.3 illustrates this connection. The researcher used Matlab and MS SQL Server, because it was available to the researcher, but can be replaced by similar products. Matlab can be replaced by Python™[1] or R Studio®[1]and MS SQL Server can be replaced by MySQL™[1].

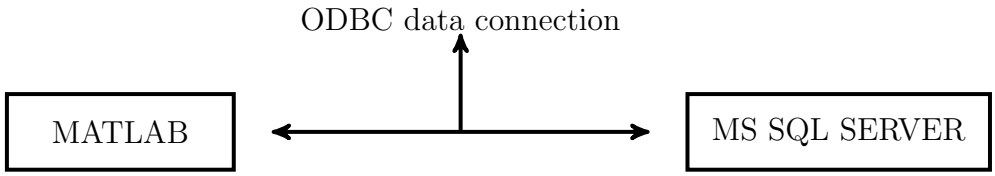


Figure 4.3: Data connection between Matlab and SQL Server

The first part of the simulator is used only once to create the initial data in the tables. Thereafter, the simulator is used to create initial records of purchasing instances in the trans-

[1]All registered trademarks will now be omitted.

action tables (Transactional History and Orders). This functionality is used within the PDO demonstrator that will be discussed in Chapter 5. The first tables populated are the primary entities: Customers, Retailers, Branches, Product Categories, Personalised Discount Off Types and Preferences. These are the simplest since they only contain list information.

4.3.1 Customers table

The customer IDs are populated from one to the number of customers participating in the system. The customer handles are populated as the entity name and the associated ID digit. For example, the customer with `CustID` as one is given the `CustHandle` *"Customer_1"*.

The `LastPurchase` date of each customer is given as an initial date at the beginning of service. After this the last purchase attribute is updated every time a customer visits a participating outlet. Except for the last purchase attribute, the Retailers, Branches, Product Categories and Preferences tables are populated in the same manner.

4.3.2 PDO Types table

There are three different types of personalised discount offers a customer can receive, thus the IDs are populated from one to three. The first `PDOTypeName` is a normal PDO, the second type is a cross-sell PDO and lastly the third type is an upsell PDO.

4.3.3 Outlets table

The IDs of the outlets identify each unique store that consist of a retailer and a branch with a unique location. An assumption is made that every branch accommodates each retailer. Thus, if five branches and five retailers are participating in this service, 25 outlets are populated. The locations are assigned as *"RetailerID_FK, BranchID_FK"* to ensure each outlet has a unique location in the model. If an outlet represents `RetailerID_FK` one and `BranchID_FK` two, the unique location would be *"1, 2"*.

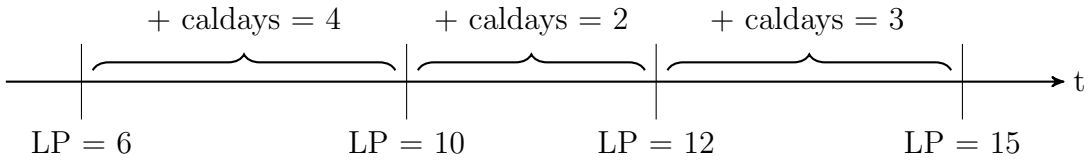
4.3.4 Orders table

This table is populated to contain a history for a certain number of days until a certain point in time. From this point onwards new order records are individually added to the Orders table and the table is updated.

The purchasing behaviour of customers are very complex and it is for this reason that the researcher simplified it to three main groups. The researcher identified the three groups based on known behaviour qualities. The first type is customers who buy their groceries monthly. These customers are also divided into a group of customers who make purchases at

Table 4.19: Customer purchasing behaviour type

Behaviour Type	Description
1	Customers purchasing at the beginning or end of the month.
	Customers purchasing in the middle of the month.
2	Customers purchasing weekly.
3	Customers purchasing two to three times a week.



LastPurchase (LP)	...
~~06-01-2016~~	...
~~10-01-2016~~	...
~~12-01-2016~~	...
15-01-2016	...

Figure 4.4: Example of the customer's last purchase date update

the beginning or end of the month and a group who purchases their monthly groceries in the middle of a month.

The second type is customers buying their groceries weekly, thus four times per month. Lastly, the third type of customers who visit stores two to three times a week which results to 10 times a month on average. These behaviour types are summarised in Table 4.19.

Based on the type of customer, certain time ranges within a month is allocated for this type of customer to visit a store, assuming each month has 30 days. The simulator thus allocate days of the month to different customers based on their purchasing behaviour type.

The Orders table is populated for each day, thus the `CustomerIDs` allocated for the specific day in the month are recorded along with the purchase date as the date at the point in simulation time. The customer's `LastPurchase` is updated with the new date in the Customers table as described in Subsection 4.3.1. Figure 4.4 visually explains the concept of updating last purchase dates for customers.

The time stamp of the order instance is created randomly. The time is between the opening and closing time of the store.

Next the respective outlet must be chosen. At first the `OutletID` was chosen with a built-in binomial Matlab function. *"binornd(N,P)"* generates random numbers from the binomial distribution with parameters specified by the number of trials, N, and probability of success for each trial, P. This seemed sufficient when the number of participating outlets in

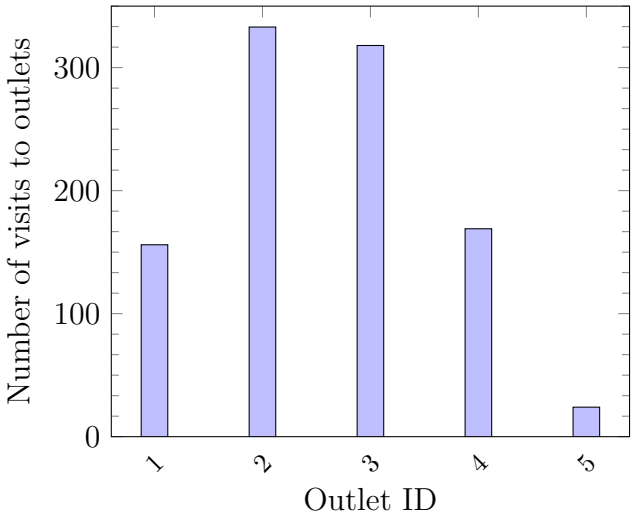


Figure 4.5: Frequency of outlets visited if outlets = 5 following a binomial distribution

the service was small and the probability of success chosen appropriately. As the number of outlets increased and the probability kept constant, the researcher found this function to be insufficient for the purpose of assigning `OutletIDs` to purchasing instances. Figure 4.5 illustrates the frequency distribution of outlets visited when the number of participating outlets is set to five.

Figure 4.6 shows the same distribution as before, but the number of participating outlets is changed to 50. It is clear to see that when the number of outlets participating in the service increases, some of the outlets are not included in the distribution. In reality this means they are not visited and this is not a realistic reflection.

The `OutletIDs` are thus chosen from a beta distribution. The standard beta distribution gives the probability density of a value x on the interval (0,1):

$$Beta(\alpha, \beta): \ prob(x|\alpha, \beta) = \frac{x^{\alpha-1}(1-x)^{\beta-1}}{B(\alpha,\beta)}, \quad 0 < x < 1$$

where B is the beta function

$$B(\alpha, \beta) = \int_0^1 t^{\alpha-1}(1-t)^{\beta-1}\mathrm{d}t.$$

A random observation is obtained from the beta distribution. Both parameters α and β were set at 1.2. The returned value from the beta distribution is multiplied by the total number of outlets registered for this service in order to scale the beta value to a value larger than zero. The value is rounded up to ensure all IDs are integers. Figure 4.7 shows the beta distribution for these parameters.

This value identifies the outlet that is visited and thus the `OutletID_FK` in the Orders table. It is clear from Figure 4.8 this method includes all outlets when the number of outlets

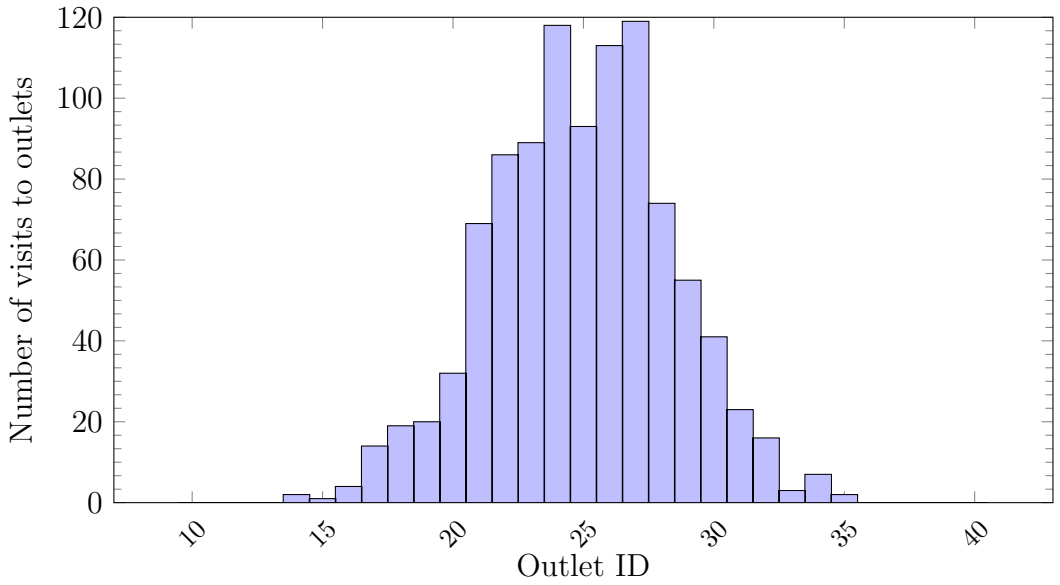


Figure 4.6: Frequency of outlets visited if outlets = 50 following a binomial distribution

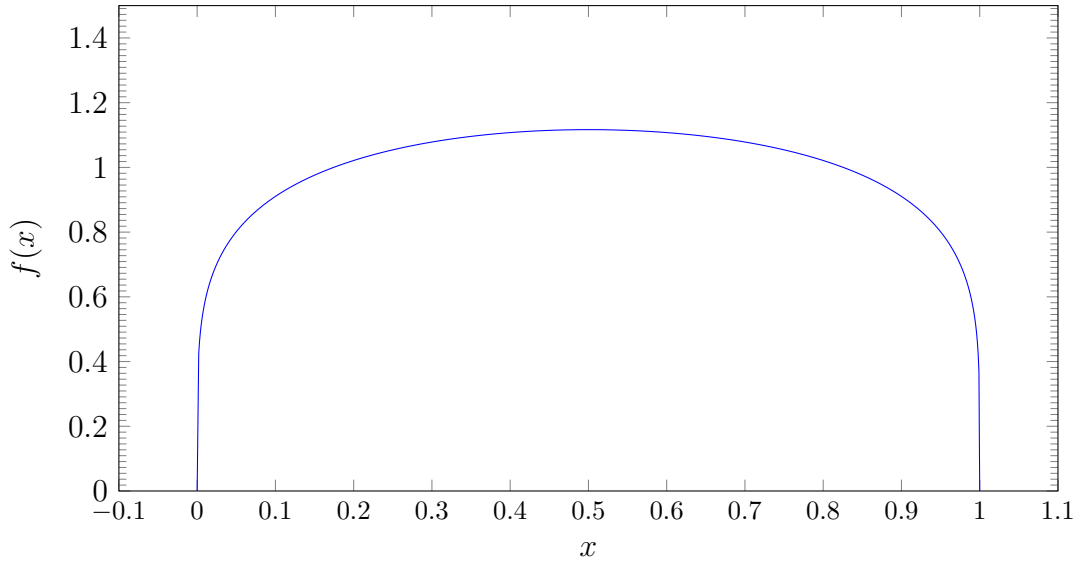


Figure 4.7: Beta distribution for identifying the Outlet IDs

is 25. The beta distribution ensures that some outlets are visited less often than others which is a realistic situation. An assumption is made that a customer only go to a store once on a specific day.

4.3.5 Products table

The ID and product name are populated in the same manner as in the Customers table. The product name represents the product *e.g. "HairBear"*. The features for the products were created using a built-in Matlab function that creates random strings and represent different

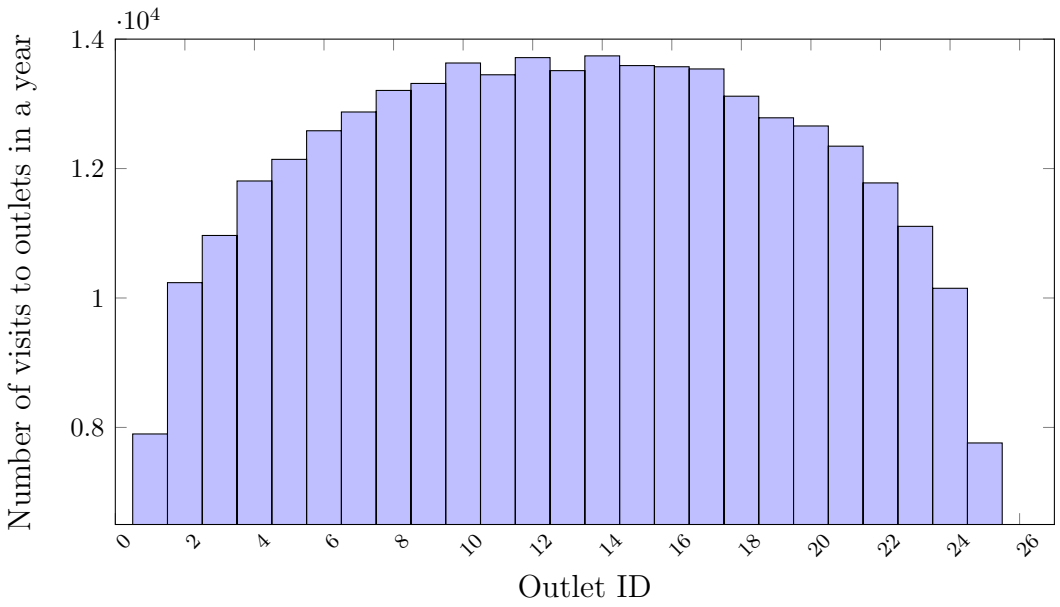


Figure 4.8: Frequency of customers' visits to outlets following a beta distribution

features for the products such as *"For curly hair"* or *"For dry hair"*.

For the unit price of the products, the attribute is randomly chosen according to a beta distribution. An assumption is made that the unit prices stay constant for the duration of the simulation. The unit prices of the products do not change as time passes as this is not the focus of this study. A pseudo-random probability is generated with a built-in Matlab function. This probability is used to sample from the beta distribution with $\alpha = 2$ and $\beta = 3$. A value between zero and one is returned. This value is then multiplied by the maximum unit price to create a unit price for a specific product. This ensures that the products' unit prices vary.

The product category of the specific product is assigned by using a built-in randomise Matlab function. The sizes of the products are distinguished between *"small"* and *"large"*. The products' sizes are assigned by looking whether the unit price of the product is smaller or larger than the average price of all the products.

4.3.6 Customers_Preferences table

This table links the customer ID with the associated preference ID. An assumption is made that each customer can have up to the maximum number of preferences available, but should have a minimum of one preference. Thus, more than one preference ID can be assigned to a specific customer ID. As explained in Subsection 4.2.2, the associative entities use the combination of the primary entities' IDs as the new compound key.

A Matlab built-in function is used to choose a random number between one and the

maximum number of preferences available. The random number returned states how many preferences a specific customer has. The preferences are randomly chosen for each customer according to the number of preferences the customer is assigned.

This is verified by investigating if the number of preferences per `CustID_FK` corresponds to the random number returned by the built-in Matlab function. Table 4.20 visualises a sample for the first five customers from the populated data in the Customers_Preference table along with the randomised number of preferences for each `CustID_FK`.

Table 4.20: Verification of Customers_Preferences table

CustID_FK	PrefID_FK
1	3
1	1
1	4
2	4
3	3
3	1
3	5
3	4
3	2
4	2
4	1
5	4
5	2
5	1

CustID_FK	Random number of preferences
1	3
2	1
3	5
4	2
5	3

4.3.7 Outlets_Products table

This table is populated in the same manner as the Customers_Preferences table explained in Subsection 4.3.6. The unique compound key is a combination of the `OutletID_FK` and the `ProductID_FK`. The assumption is made that every product is available in each outlet. The other unique attributes in this table are the `XYLocation` and the `SOH`. The `XYLocation` is used to locate a specific product in a given outlet. The locations of the products are assigned in the same manner as the outlet locations in Subsection 4.3.3. So for example, if `OutletID_FK` is three and `ProductID_FK` is five, the assigned `XYLocation` is *"3, 5"*. This ensures that each product in each assorted outlet has a unique `XYLocation` in this study.

The stock on hand (SOH) for the different products are assigned following a beta distribution. The SOH value is assigned in the same manner as the unit price in Subsection 4.3.5.

A random probability is used to sample from the beta distribution with $\alpha = 3$ and $\beta = 2$. The value returned between zero and one is multiplied by the maximum number of products to assign the SOH value for each individual product. An assumption is made that there is always SOH and the SOH is manually updated as orders arrive and is excluded from the scope of this study.

4.3.8 Transactional History table

The Transactional History table is populated based on the Orders table. For each `OrderID` in the Orders table, a transactional history is created. This table states each product that a customer acquires with each order, as well as the quantity and the price the customer paid for it.

Depending on the customer purchasing behaviour type explained in Table 4.19, various number of items are bought by the customers. Every customer has a base basket which contains products that are bought regularly. An assumption is made that any customer can buy any product at any participating outlet.

The quantity of each product is chosen being one, two or three and having weights of 0.5, 0.3 and 0.2 respectively. The stock on hand for the acquired products is also updated in the Outlets_Products table.

The unit price of the specified product is obtained from the Products table. In the event where discount is received the `UnitPrice` attribute in the Transactional History table will take the discount into account. The transactional information contained in this table is vital regarding the purchasing behaviour of a customer. This information will be used by the PDO predictor in the PDO demonstrator that will identify individual personalised discount offers in Chapter 5.

4.3.9 Personalised Discount Offers, Personalised Discount Offers Accepted, Personalised Discount Offers Rejected and Personalised Discount Offers Origin tables

These four tables are created during this part of the study. However, these tables are not populated by the simulator. The tables will be used in the next part of the study, which is the PDO demonstrator. The PDO identified by the PDO predictor will be recorded in the Personalised Discount Offers table. This table will identify each unique offer by having a `PDOID`. Each ID will be assigned the product and to whom the offer is presented, along with the discount applicable. The PDO type is recorded based on the type of offer presented. The PDO table includes a status attribute which is zero or one. The zero status represents the rejection of an offer. A status of one indicates the acceptance of an offer.

If a customer accepts an offer, the `PDOID` is assigned to the `THID` from the Transactional History table where the specified product is acquired and the discount is applied. This event is recorded in the Personalised Discount Offers Accepted table. If the customer rejects an offer, the `PDOID` is assigned to the `OrderID` from the Orders table which specifies information regarding the purchase instance of the customer. As with the acceptance event, the rejection event is recorded in the Personalised Discount Offers Rejected table.

When a PDO was a cross-sell or upsell offer based on another product, the product from which the cross-sell or upsell originated is recorded in the Personalised Discount Offers Origin table where the `PDOID_FK` refers to the PDO proposed to the customer and `ProductID_FK` refers to the product from where the cross-sell or upsell offer originated. These two primary keys from other tables serve as the new compound key in this table. The population of these tables are the fundamental elements of the PDO demonstrator.

4.4 Chapter 4 summary

This chapter presents the design and development of the simulator. The simulator is used for generating pseudo-customer data in this study, the main reason for which is overcoming ethical issues. The simulator is designed using methods from Kendall and Kendall (2014). Using the design stage of the simulator, the researcher was able to develop the simulator using Matlab and MS SQL Server.

The design and development stage of the simulator was an iterative process and for such an intricate system, the researcher found it wise to first create the tables with only few records. This was done to ensure the answers are controllable and predictable for validation purposes. It is essential for the information simulated in this part of the study to be correct since it is employed in the PDO demonstrator, which is the topic of discussion in the following chapter.

Chapter 5

Design and development of the PDO demonstrator

The previous chapter informed the reader about the design and development of the simulator. The simulator creates pseudo-customer historical data, which will now be used in the PDO demonstrator. This chapter represents the design and development of the PDO demonstrator in order to propose personalised discount offers to customers. This chapter will start with the methodology used, followed by the design and development of the system. Lastly, the chapter will explain the process of onboarding a new customer to the system.

5.1 PDO demonstrator design and development methodology

This chapter initiates the third phase of the research methodology identified in Section 1.5. This phase can be divided into two sub-phases namely 1) the design and 2) the development of the PDO demonstrator. During the design sub-phase the researcher must identify approaches to predict and propose PDOs to customers. These alternatives must be evaluated and the most appropriate one will be utilised as the PDO predictor within the PDO demonstrator. The researcher must then investigate cross-sell and upsell techniques and how to apply them in the PDO demonstrator.

Once these factors have been determined, the second sub-phase of the PDO demonstrator can commence, which is the development of the PDO demonstrator. Lastly, the researcher will investigate the process of on-boarding a new customer in the system.

5.2 Design of the PDO demonstrator

The goal of the *demonstrator* is to analyse customer transactional history using the PDO predictor and propose *personalised discount offers* (PDOs) to applicable customers based on products bought periodically. Figure 5.1 illustrates a product with a *periodical tendency*. Number one to five show the instances when the product was purchased and the $\triangle T_i$ indicate the times between two subsequent purchases. When the $\triangle T_i$ of all purchases are relatively the same, the product has a periodical tendency.

The PDO demonstrator can be divided into two parts based on functionality. The first part consists of the analysis of the historical customer data that will identify potential PDOs

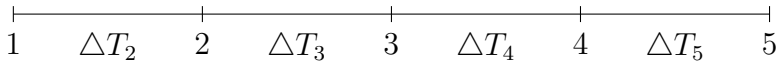


Figure 5.1: Example of a product with a periodical tendency

to be proposed to the relevant customer and is represented as the PDO predictor within the PDO demonstrator.

The second part includes the partial functionality of the simulator, which provides the continued simulation of customer purchases to generate transactional history. The functionalities of the PDO demonstrator are summarised in Figure 5.2 and the following subsection contains the discussion of the various analysis approaches for the PDO predictor.

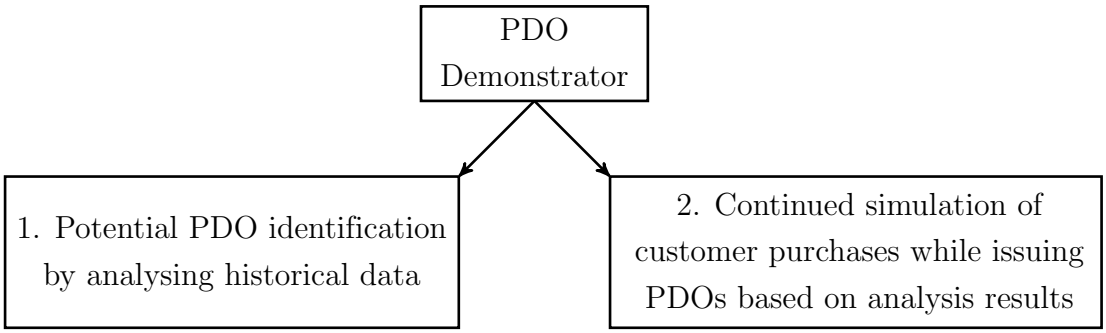


Figure 5.2: Schematic view of PDO demonstrator functionalities

No existing approaches were found to determine the next purchase date for FMCG having a periodical tendency. Existing loyalty programmes provide "personalised" offers based on the behaviour of similar customers or customer segments. The researcher wanted to investigate different analytical approaches to identify the next purchase date for these types of products.

5.2.1 Analytical approaches for the PDO predictor

The PDO predictor must analyse transactional history of a specific customer to propose appropriate PDOs to that customer. The PDO predictor should predict the potential *next purchase date* (NPD) of a product based on prior acquisitions by the customer. The NPD is a proposed date on which the customer might purchase the product again. Various options are available for this analysis. This study evaluated three approaches to predict the NPD: 1) the arithmetical average approach, 2) the weighted average approach and lastly, 3) the repurchase curve approach. The latter is an adaptation of survival analysis and is more sophisticated than the first two proposed techniques. They are theoretically discussed in Subsections 5.2.1.1 to 5.2.1.3 below.

5.2.1.1 Arithmetical average approach

The *arithmetical average approach* (AAA) is a simple approach to find the NPD of a product that is bought periodically by a specific customer. The duration in days between two subsequent acquisitions of the analysed product is determined and denoted as $\triangle T_i$, where i represents the i-th purchase instance. After this, the duration (between the two transactions) is divided by the quantity of the earlier transaction, as shown in (5.1). This calculation provides an estimate of the customer's usage of the product. The result is measured in the unit of *days per product*:

$$X_i = \frac{\triangle T_i}{\text{Qty}_{i-1}}. \tag{5.1}$$

The overall average of Customer Z's usage given in *days per product* is calculated by taking the average of all X_i values. $\overline{X}_i$ represents the average days per product at purchase instance i. Using this answer one can estimate when the customer would likely need to buy more of the product. Figure 5.3 explains the calculation of the average NPD of a specific product, Product Y.

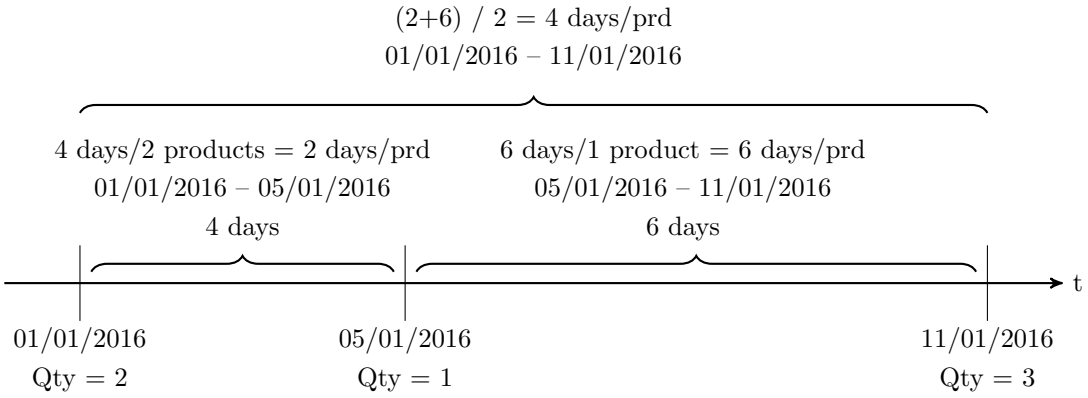


Figure 5.3: Arithmetic average calculation of next purchase date

From this analysis one can see that the average days per product for Customer Z at purchase instance i ($\overline{X}_i$) for Product Y was calculated as four days per product. The last quantity purchase of Product Y was three. Thus, using the average days per product ($\overline{X}_i$) at purchase instance i and the quantity, one can estimate that the NPD will be in 12 days' time (4 days/prod $\times$ 3 products). The NPD in this example would be 23/01/2016.

To improve the efficiency of this technique, the researcher used a recursive average equation proposed by Ross (2013) in order to calculate the overall average faster. The recursive equation for the average can be seen in (5.2) and can only be calculated if $i \geq 2$.

With $\overline{X}_1 = 0$, the general expression is

$$\overline{X}_j = \overline{X}_{j-1} + \frac{X_j - \overline{X}_{j-1}}{j}. \tag{5.2}$$

The expected NPD of a certain product can be calculated using (5.3) along with the average days per product at instance i ($\overline{X}_i$) taking into account the product usage of the customer,

$$\text{NPD}_i = \text{Purchase Date}_i + (\overline{X}_i \times \text{Qty}_i). \tag{5.3}$$

The researcher wanted to investigate the influence of the quantity in the analysis using the AAA. For this (5.1) will change to (5.4) and will be measured in the unit of *days*:

$$X_i = \triangle T_i. \tag{5.4}$$

The overall average of the customers usage is calculated as the average of all the X_i values using (5.2) at purchase instance i. The expected NPD of a specific product after purchase instance i will be calculated as

$$\text{NPD}_i = \text{Purchase Date}_i + \overline{X}_i. \tag{5.5}$$

The researcher simulated a test dataset using the simulator and investigated the influence of the quantity on the prediction of the NPD and when the customer actually acquired the product. This test dataset will be illustrated taking Product Y purchased by Customer Z as an example in Table 5.1.

Table 5.1: Customer Z's Product Y transactional history and AAA NPD prediction

Cust Z Prod Y			**AAA including quantity**						**AAA excluding quantity**			
i	**Date**	**Qty**	$\triangle T_i$	X_i	$\overline{X}_i$	$\overline{X}_i * \mathbf{Qty}_i$	**NPD** (5.3)	**Difference**	$\triangle T_i$	$\overline{X}_i$	**NPD** (5.5)	**Difference**
1	17-Jan-16	2			0					0		
2	15-Feb-16	1	29	14.50	7.25	7.25	22-Feb-16	23	29	14.50	29-Feb-16	16
3	15-Mar-16	3	29	29.00	14.50	43.50	27-Apr-16	10	29	19.33	03-Apr-16	14
4	17-Apr-16	1	33	11.00	13.63	13.63	30-Apr-16	19	33	22.75	09-May-16	10
5	19-May-16	1	32	32.00	17.30	17.30	05-Jun-16	11	32	24.60	12-Jun-16	4
6	16-Jun-16	1	28	28.00	19.08	19.08	05-Jul-16	10	28	25.17	11-Jul-16	4
7	15-Jul-16	2	29	29.00	20.50	41.00	25-Aug-16	12	29	25.71	09-Aug-16	4
8	13-Aug-16	3	29	14.50	19.75	59.25	11-Oct-16	25	29	26.13	08-Sep-16	8
9	16-Sep-16	2	34	11.33	18.81	37.63	23-Oct-16	9	34	27.00	13-Oct-16	1
10	14-Oct-16	3	28	14.00	18.33	55.00	08-Dec-16	24	28	27.10	10-Nov-16	4
11	14-Nov-16	1	31	10.33	17.61	17.61	01-Dec-16	12	31	27.45	11-Dec-16	2
12	13-Dec-16	1	29	29.00	18.56	18.56	31-Dec-16	11	29	27.58	09-Jan-17	2
13	11-Jan-17	1	29	29.00	19.36	19.36	30-Jan-17	10	29	27.69	07-Feb-17	3
14	10-Feb-17	2	30	30.00	20.12	40.24	22-Mar-17	10	30	27.86	09-Mar-17	3
15	12-Mar-17	3	30	15.00	19.78	59.33	10-May-17	29	30	28.00	09-Apr-17	2
16	11-Apr-17	3	30	10.00	19.17	57.50	07-Jun-17	24	30	28.13	09-May-17	4
17	13-May-17	1	32	10.67	18.67	18.67	31-May-17	13	32	28.35	10-Jun-17	3
18	13-Jun-17	2	31	31.00	19.35	38.70	21-Jul-17	10	31	28.50	11-Jul-17	0
19	11-Jul-17	1	28	14.00	19.07	19.07	30-Jul-17	11	28	28.47	08-Aug-17	3
20	11-Aug-17	1	31	31.00	19.67	19.67	30-Aug-17	7	31	28.60	08-Sep-17	1
21	07-Sep-17	1	27	27.00	20.02	20.02	27-Sep-17	11	27	28.52	05-Oct-17	3
22	08-Oct-17	1	31	31.00	20.52	20.52	28-Oct-17	7	31	28.64	05-Nov-17	0

Continued on next page

Table 5.1 continued

Cust Z Prod Y			AAA including quantity						AAA excluding quantity			
i	Date	Qty	$\triangle T_i$	X_i	$\overline{X}_i$	$\overline{X}_i * \text{Qty}_i$	NPD (5.3)	Difference	$\triangle T_i$	$\overline{X}_i$	NPD (5.5)	Difference
23	05-Nov-17	3	28	28.00	20.84	62.52	06-Jan-18	27	28	28.61	03-Dec-17	6
24	09-Dec-17	1	34	11.33	20.44	20.44	29-Dec-17	5	34	28.83	06-Jan-18	2
25	04-Jan-18	3	26	26.00	20.67	62.00	07-Mar-18	31	26	28.72	01-Feb-18	5
26	06-Feb-18	2	33	11.00	20.29	40.59	18-Mar-18	12	33	28.88	06-Mar-18	0
27	06-Mar-18	3	28	14.00	20.06	60.19	05-May-18	29	28	28.85	03-Apr-18	3
28	06-Apr-18	1	31	10.33	19.71	19.71	25-Apr-18	11	31	28.93	04-May-18	2
29	06-May-18	3	30	30.00	20.07	60.21	05-Jul-18	31	30	28.97	03-Jun-18	1
30	04-Jun-18	3	29	9.67	19.72	59.17	02-Aug-18	25	29	28.97	02-Jul-18	5
31	07-Jul-18	2	33	11.00	19.44	38.88	14-Aug-18	9	33	29.10	05-Aug-18	0
32	05-Aug-18	1	29	14.50	19.29	19.29	24-Aug-18	8	29	29.09	03-Sep-18	1
33	02-Sep-18	1	28	28.00	19.55	19.55	21-Sep-18	11	28	29.06	01-Oct-18	1
34	02-Oct-18	1	30	30.00	19.86	19.86	21-Oct-18	14	30	29.09	31-Oct-18	5
35	05-Nov-18	1	34	34.00	20.26	20.26	25-Nov-18	8	34	29.23	04-Dec-18	1
36	03-Dec-18	2	28	28.00	20.48	40.95	12-Jan-19		28	29.19	01-Jan-19	
								15.26				**3.62**

From Table 5.1, it can be derived that quantity has an influence on the NPD prediction. The *difference* columns in Table 5.1 indicate the absolute difference in days between the NPD that was predicted and the actual date Customer Z purchased Product Y. Looking at line $i = 8$ of Table 5.1 the AAA including quantity estimates an NPD of 11-Oct-16 and the AAA excluding quantity an NPD of 08-Sep-16. The actual purchase date is shown in $i = 9$, which was on 16-Sep-16. The two approach alternatives had differences of 25 days and 8 days respectively. Other values in the difference columns shows that the AAA excluding the quantity predicts the NPD with a smaller absolute difference than the AAA including the quantity.

The means of the difference columns are shown at the bottom of Table 5.1. These values indicate that excluding the quantity in the AAA calculations provide better NPD predictions. The ultimate goal is to minimise the absolute difference between the NPD predicted and the actual purchase date.

While the AAA model that excludes the quantity provided stronger results, the influence of quantity on the calculation cannot be ignored. The researcher therefore decided to compare the AAA with another analytical approach to see if accuracy improves. A weighted average approach will be explored next.

5.2.1.2 Weighted average approach

Using the similar principles as the AAA, the researcher investigated the possibility of using a *weighted average approach* (WAA) to calculate the possible NPD of a customer-product pair. The weighted average was calculated as seen in (5.6) where $\overline{X}_i$ represents the average days per product calculated at purchase instance i,

$$\overline{X}_i = \frac{\sum(\triangle T_i \times \text{Qty}_{i-1})}{\sum \text{Qty}_{i-1}}. \tag{5.6}$$

The NPD is calculated in the same manner as the AAA calculation in (5.3),

$$\text{NPD}_i = \text{Purchase Date}_i + (\overline{X}_i \times \text{Qty}_i).$$

The researcher also investigated the influence of excluding quantity in the NPD calculation using the WAA. The NPD calculation which excludes the quantity is the same as in (5.5) and is denoted as

$$\text{NPD}_i = \text{Purchase Date}_i + \overline{X}_i.$$

The researcher conducted preliminary experiments on the same test dataset used in the AAA calculations in Table 5.1. The WAA calculations, seen in Table 5.2, include both calculations for including and excluding quantity when predicting the NPD. The *difference* columns

indicate the absolute difference between the NPD predicted for Product X and the actual date Customer Z bought Product X.

Lines $i = 7$–10 for example the WAA including the quantity in the NPD calculation had much larger differences comparing to the NPD calculation which excludes quantity. This occurs everytime the quantity value is larger than one. This can be an indication that Customer Z purchased Product Y periodically without any relation to the quantity previously bought.

By inspecting the other values in the difference columns it is clear to see that by including the quantity in the NPD predictions using the WAA is not as close to the actual purchase date as the NPD prediction excluding the quantity. At the bottom of Table 5.2 the means of the difference columns are calculated and one can see that by excluding the quantity more accurate predictions can be made.

Table 5.2: Customer Z's Product Y transactional history and WAA NPD prediction

Cust Z Prod Y			**Weighted Average Approach**				**Including Quantity**		**Excluding Quantity**	
i	**Date**	**Qty**	$\triangle T_i$	$\sum(\triangle T_i \times \mathbf{Qty}_{i-1})$	$\sum \mathbf{Qty}_{i-1}$	$\overline{X}_i$	**NPD** (5.2.1.2)	**Difference**	**NPD** (5.2.1.2)	**Difference**
1	17-Jan-16	2			2			0		
2	15-Feb-16	1	29	58.00	3	29.00	15-Mar-16	0.00	15-Mar-16	0.00
3	15-Mar-16	3	29	87.00	6	29.00	10-Jun-16	53.00	13-Apr-16	4.00
4	17-Apr-16	1	33	186.00	7	31.00	18-May-16	1.00	18-May-16	1.00
5	19-May-16	1	32	218.00	8	31.14	19-Jun-16	3.00	19-Jun-16	3.00
6	16-Jun-16	1	28	246.00	9	30.75	16-Jul-16	1.00	16-Jul-16	1.00
7	15-Jul-16	2	29	275.00	11	30.56	14-Sep-16	31.00	14-Aug-16	1.00
8	13-Aug-16	3	29	333.00	14	30.27	11-Nov-16	55.00	12-Sep-16	4.00
9	16-Sep-16	2	34	435.00	16	31.07	17-Nov-16	33.00	17-Oct-16	3.00
10	14-Oct-16	3	28	491.00	19	30.69	14-Jan-17	60.00	13-Nov-16	1.00
11	14-Nov-16	1	31	584.00	20	30.74	14-Dec-16	1.00	14-Dec-16	1.00
12	13-Dec-16	1	29	613.00	21	30.65	12-Jan-17	1.00	12-Jan-17	1.00
13	11-Jan-17	1	29	642.00	22	30.57	10-Feb-17	0.00	10-Feb-17	0.00
14	10-Feb-17	2	30	672.00	24	30.55	12-Apr-17	30.00	12-Mar-17	0.00
15	12-Mar-17	3	30	732.00	27	30.50	11-Jun-17	60.00	11-Apr-17	0.00
16	11-Apr-17	3	30	822.00	30	30.44	11-Jul-17	58.00	11-May-17	2.00
17	13-May-17	1	32	918.00	31	30.60	12-Jun-17	1.00	12-Jun-17	1.00
18	13-Jun-17	2	31	949.00	33	30.61	13-Aug-17	32.00	13-Jul-17	2.00
19	11-Jul-17	1	28	1005.00	34	30.45	10-Aug-17	1.00	10-Aug-17	1.00
20	11-Aug-17	1	31	1036.00	35	30.47	10-Sep-17	3.00	10-Sep-17	3.00
21	07-Sep-17	1	27	1063.00	36	30.37	07-Oct-17	1.00	07-Oct-17	1.00
22	08-Oct-17	1	31	1094.00	37	30.39	07-Nov-17	2.00	07-Nov-17	2.00
23	05-Nov-17	3	28	1122.00	40	30.32	03-Feb-18	54.00	05-Dec-17	4.00
24	09-Dec-17	1	34	1224.00	41	30.60	08-Jan-18	4.00	08-Jan-18	4.00
25	04-Jan-18	3	26	1250.00	44	30.49	05-Apr-18	59.00	03-Feb-18	3.00
26	06-Feb-18	2	33	1349.00	46	30.66	08-Apr-18	32.00	08-Mar-18	2.00
27	06-Mar-18	3	28	1405.00	49	30.54	05-Jun-18	59.00	05-Apr-18	1.00

Continued on next page

Table 5.2 continued

Cust Z Prod Y			**Weighted Average Approach**				**Including Quantity**		**Excluding Quantity**	
i	**Date**	**Qty**	$\triangle T_i$	$\sum(\triangle T_i \times \mathbf{Qty}_{i-1})$	$\sum \mathbf{Qty}_{i-1}$	$\overline{X}_i$	**NPD** (5.2.1.2)	**Difference**	**NPD** (5.2.1.2)	**Difference**
28	06-Apr-18	1	31	1498.00	50	30.57	06-May-18	0.00	06-May-18	0.00
29	06-May-18	3	30	1528.00	53	30.56	05-Aug-18	61.00	05-Jun-18	1.00
30	04-Jun-18	3	29	1615.00	56	30.47	03-Sep-18	56.00	04-Jul-18	3.00
31	07-Jul-18	2	33	1714.00	58	30.61	06-Sep-18	31.00	06-Aug-18	1.00
32	05-Aug-18	1	29	1772.00	59	30.55	04-Sep-18	2.00	04-Sep-18	2.00
33	02-Sep-18	1	28	1800.00	60	30.51	02-Oct-18	0.00	02-Oct-18	0.00
34	02-Oct-18	1	30	1830.00	61	30.50	01-Nov-18	4.00	01-Nov-18	4.00
35	05-Nov-18	1	34	1864.00	62	30.56	05-Dec-18	2.00	05-Dec-18	2.00
36	03-Dec-18	2	28	1892.00	64	30.52	02-Feb-19		02-Jan-19	
							Average:	**23.26**		**1.74**

Table 5.3: Comparison between AAA and WAA when including and excluding quantity from NPD prediction for Customer Z's Product X

Mean absolute difference between NPD and purchase date	**AAA**	**WAA**
Including quantity	15.26	23.26
Excluding quantity	3.62	1.74

The mean absolute difference must ultimately be minimised in order to provide accurate predictions. To evaluate whether the AAA and the WAA provide possible solutions to calculate the NPD of products, the researcher constructed Table 5.3 using the mean absolute differences calculated in Table 5.1 and Table 5.2 to compare these two analysis approaches.

After reviewing Table 5.3 it is evident that the quantity should not be included in the NPD calculations for both analysis approaches in the context of this study. With mean absolute differences of 15.26 days and 23.26 days, the NPDs are mostly predicted too early or too far in the future with regards to the actual time the customer would be susceptible to buy the product. By excluding the quantity from the NPD predictions the mean absolute differences are smaller for both the analysis approaches. Comparing the two analysis approaches it would seem that the WAA provide a better NPD prediction with only a 1.74 days mean absolute difference where the AAA obtained a NPD prediction with a 3.62 days mean absolute difference.

The researcher wanted to investigate whether a more sophisticated approach exists and would provide better results. This is discussed in the next subsection.

5.2.1.3 Repurchase curve analysis approach

The researcher searched for more sophisticated approaches to analyse and estimate an NPD for products. Survival analysis is used to analyse the time to a specific event or occurrence as explained in Subsection 2.6.5. This is also referred to as the reliability analysis in the maintenance domain.

Survival analysis is fixed to a specific time period and takes account of the various factors influencing the timing of an event. No other factors influencing repurchases are included in the study and the analysed time is continued as time passes it is difficult to use the standard approach of survival analysis as done in literature. The researcher applied the principle of using a survival curve to analyse and estimate an NPD for the application as it is needed in the study. From this point onwards, this curve will be referred to as the *repurchase curve* since it is not generated in the same manner as survival curves within literature.

The researcher was required to do precalculations to create a repurchase curve for each product and customer based on the usage of the customer. This will be explained through

an example: Product Y purchased by Customer Z. At first $\triangle T_i$ is calculated as the duration between subsequent purchases of the product. This value is measured in *days* and is calculated for all the purchasing instances of Product Y by Customer Z. The frequency of each $\triangle T_i$ value is determined and illustrated in Figure 5.4.

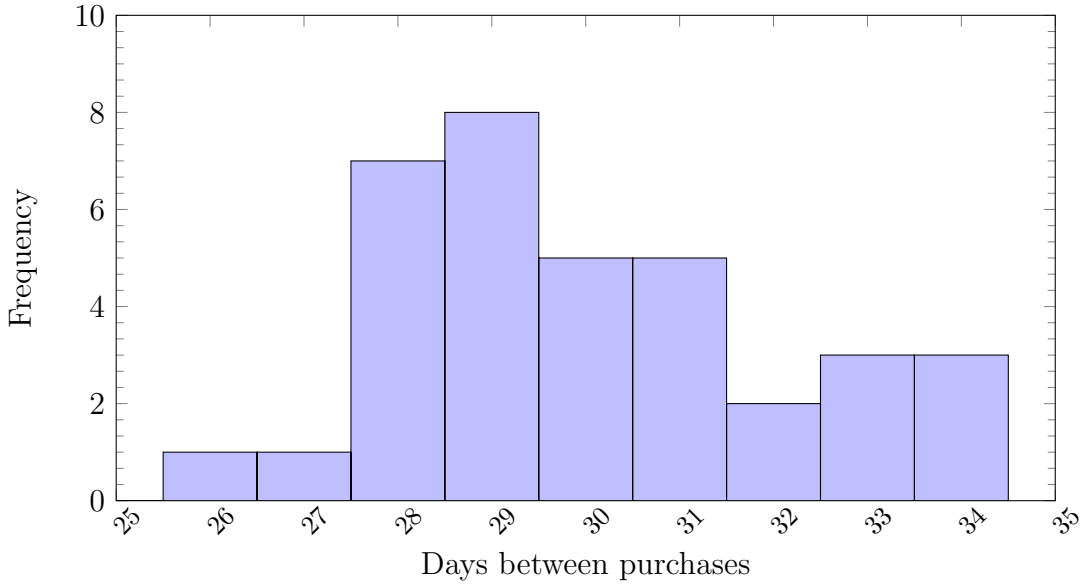


Figure 5.4: Frequency of $\triangle T_i$ values

Using these frequencies, an empirical distribution is created for Product Y by dividing each frequency by the total number of $\triangle T_i$ values. Once the probability of each $\triangle T_i$ value occurring is calculated, a cumulative probability distribution can be determined. Figure 5.5 illustrates the cumulative probability function of Product Y. This function represents the number of days within which the customer could possibly buy the product again given a certain probability. Given a cumulative probability of 0.75 the number of days between purchases is 32 days. It is with 75% certainty that Customer Z could buy Product Y within 32 days since his last purchase.

The repurchase curve of a product can be created by subtracting the cumulative probability function values from 1 to form the repurchase curve. The values for Product Y are shown in Figure 5.6. The repurchase curve is used to find the number of days from the previous purchase date on which Customer Z will not buy Product Y again based on a *repurchase probability* that is chosen. Given a repurchase probability of 0.8 the number of days between purchase is 28 days. It is therefore with 80% probability that Customer Z will buy Product Y only after 28 days from his previous purchase.

The repurchase curve is used to estimate the days between purchases for a specific product based on a given repurchase probability. The average product usage of the customer makes it possible to know the applicable time to propose a PDO to the customer. In this example the

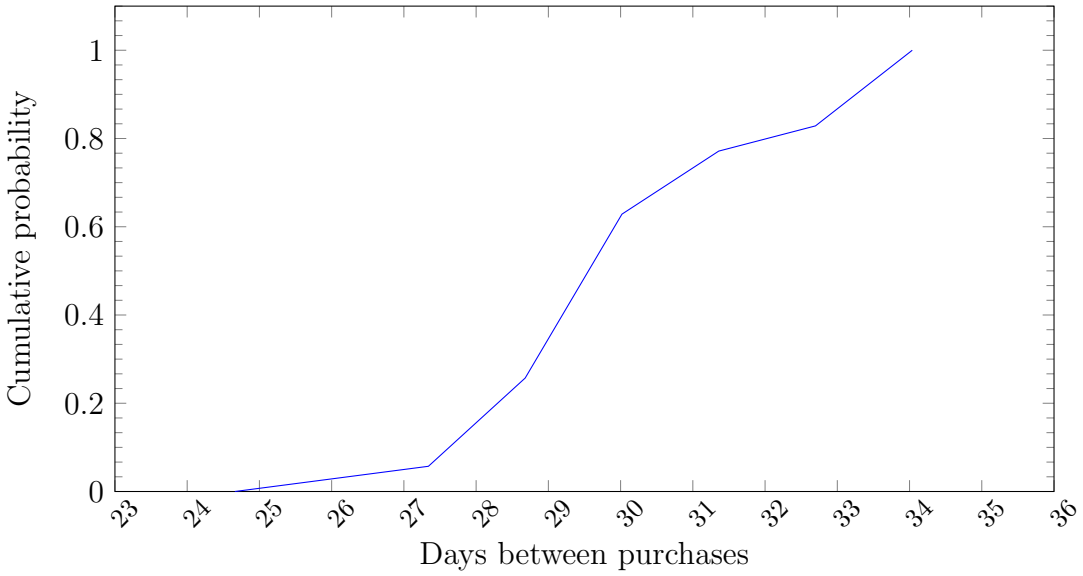


Figure 5.5: Cumulative probability of days between purchases for Product Y

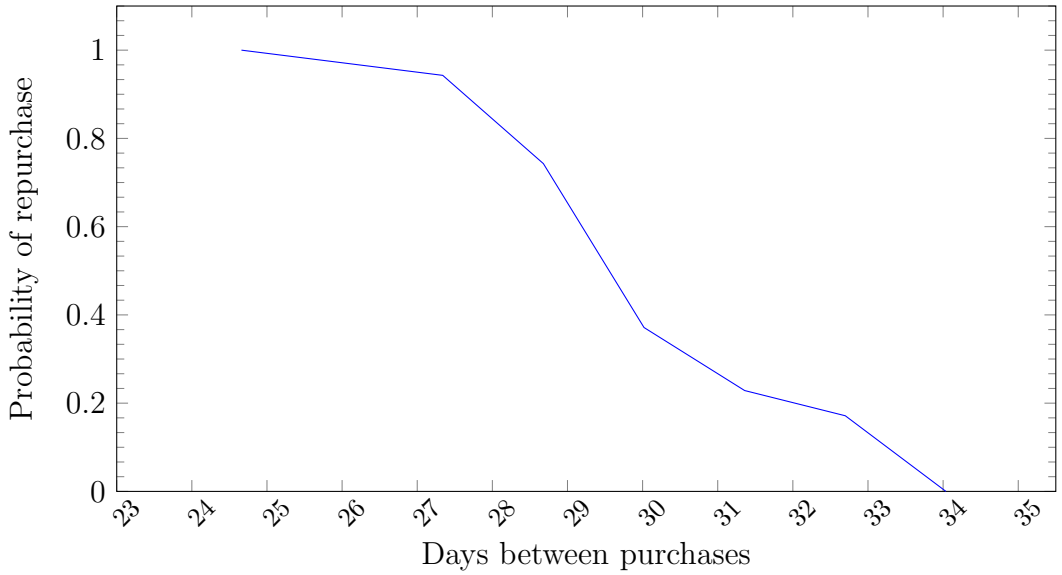


Figure 5.6: Repurchase probability of days between purchases for Product Y

days between purchases are based on a 80% probability that Customer Z will buy Product Y only after 28 days. The NPD date will be calculated in the same manner as with the previous analyses,

$$\text{NPD}_i = \text{Purchase Date}_i + X_i, \tag{5.7}$$

where X_i is estimated from the repurchase curve at a probability of 0.8 at purchase instance i.

In order to compare and evaluate the WAA, which proved to be superior to the AAA, with

the *repurchase curve analysis approach* (RCAA) some experiments will be conducted. This comparison and evaluation will be discussed in Subsection 5.2.3. Before this the design of the PDO predictor must first be addressed and follows in the next section.

5.2.2 Design of the PDO predictor

The different NPD-analysis approaches discussed in Subsections 5.2.1.2 to 5.2.1.3 provide the potential analysis approaches to estimate the potential NPD of a product. The NPD is of interest because the PDO demonstrator will propose PDOs based on the potential NPD identified for each customer-product pair. To propose a PDO for a specific product to a customer, the customer must enter any participating outlet within a given time range of the NPD predicted for the specific product.

The purpose of the system is to propose PDOs to customers on products they buy periodically. To identify these products, rule-based decision-making is used, which is based on `IF-THEN` rules used for decision-making. An `IF-THEN` rule is expressed in the form

`IF` *condition* `THEN` *conclusion.*

The rules can also include multiple *conditions* that must be met and these conditions are joined by an `AND` function. The PDO predictor must identify products that are bought periodically by a customer as well as the time the customer would potentially buy it again. For this two conditions were identified by the researcher.

The first condition is the *frequency* of the customer-product pair purchases. At least three historical purchases are needed to draw a straight-line repurchase curve. The researcher therefore decided to define the frequency of customer-product pairs to five, after which they can receive PDOs. This is to ensure four data points are available to draw a repurchase curve. For both the AAA and WAA a minimum frequency of two is needed, but was also chosen at four for consistency between the analysis approaches. The minimum frequency can be increased to test the sensitivity of the PDO predictor, but this is excluded from this study.

The second condition is to determine if a customer-product pair has a *periodic tendency* and if the customer would be susceptible to buy the product again. Customers buy certain products periodically, but not on the same day. A time range is introduced to account for the periodic customer-product pairs being eligible for PDOs. A customer would be susceptible to a periodic product when the time since the last purchase of a product by a specific customer is within a certain range of the average time between purchases for the particular product. This concept is visualised by Figure 5.7. The red area is the time range in which the PDO would be proposed based on the NPD predicted. If the product is purchased outside this red range no PDO would be proposed and the prediction would be classified as wrong.

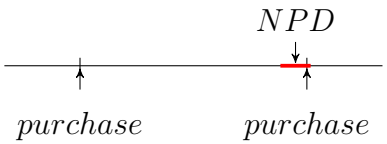


Figure 5.7: Example of a PDO within range of the NPD

The rule-based decision-making to determine whether or not a PDO should be proposed can be formulated as

$$\texttt{IF}\quad \text{Freq} \geq 5\quad \texttt{AND}\ X_i \geq \triangle T_i - \text{ range}\quad \texttt{AND}\ X_i \leq \triangle T_i + \text{ range}$$
$$\texttt{THEN}\ \text{propose PDO.}$$

The X_i is determined at a given repurchase probability for the RCAA and is the weighted average with the WAA as described in Subsection 5.2.1.

The researcher designed the PDO predictor to include cross-sell and upsell products. The PDO predictor is designed to have a 30% chance of proposing a cross-sell or upsell product as a PDO given a value from a uniform distribution, otherwise a normal PDO will be proposed.

The researcher considered using *Market Basket Analysis* (MBA) explained in Subsection 2.6.2 to identify the cross-sell or upsell products. Products identified as regularly being purchased together have the possibility of having the same NPD which makes the cross-sell or upsell opportunity not applicable. MBA can be used for other marketing strategies such as placing products with strong associations together on shelves.

The researcher constructed a relationship-matrix, shown in Figure 5.8, to identify products that can be cross-sell and upsell products based on their relationship with other products. This was constructed in such a way that some product categories can be cross-sell offers to others, but not *vice versa*. It also ensures that products are upsell products within the same product category. The researcher also incorporated the logic that a product that belongs to the base basket of a customer should not be considered for cross-sell or upsell offers since it is already part of the customer purchasing behaviour.

$$C = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1j} \\ x_{11} & x_{12} & \dots & x_{1j} \\ \vdots & \vdots & \ddots & \vdots \\ x_{i1} & x_{i2} & \dots & x_{ij} \end{bmatrix}$$

Figure 5.8: Relationship-matrix

The matrix is a P-by-P matrix where P is the total number of products and is filled with zeroes and ones. If row i and column j's intersection contains a one it presents the relationship

that product i can be a cross-sell or upsell to product j otherwise the intersection would contain a zero. The researcher constructed the matrices in such a way that each customer has their own cross-sell and upsell matrix based on their behaviour. From the example matrix in Figure 5.9, one can see that Product 1 can be cross-selled or upselled to Product 2, but not the other way around.

$$C = \begin{bmatrix} 0 & 1 & \dots & 0 \\ 0 & 0 & \dots & 1 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 1 & \dots & 0 \end{bmatrix}$$

Figure 5.9: Example of a relationship-matrix

In the case of a cross-sell or upsell PDO, a value is drawn from a standard normal distribution to determine whether it will be a cross-sell or upsell opportunity. If the value is larger than 0 the PDO will be a cross-sell product. Another product in a product category that has a relationship with Product Y will be proposed as a cross-sell PDO at a discounted price given the customer buys Product Y. Otherwise, an upsell will be proposed.

The upsell product will be a more expensive or larger product from the product category as Product Y, and proposed as an upsell PDO at a discounted price. If Product Y is the most expensive product within the product category, no PDO will be given. If the upsell PDO is accepted the product from which the upsell originated will be removed from the base basket. The percentages used in the design of the PDO predictor were selected by the researcher with support from a research supervisor. This can be amended by the enterprise providing this service.

The PDO demonstrator will emulate a real world event where the customer accepts or rejects the offer. If a normal PDO is proposed the acceptance rate would be 100% since the product is part of the base basket and would not be purchased at full price if a discount is available. The researcher decided to design the demonstrator using a 50% chance of the customer accepting or rejecting a cross-sell or upsell offer. The researcher used this percentage as a starting point as it is inadequate to assume the probability of accepting an offer increases based on the acceptance history of the customer. The offer could be a cross-sell or upsell offer and based on the customer's experience with the new product they might not accept this offer again. This percentage will be determined by the acceptance and rejection rate of the customers in real life and will thus be determined by analysing their historical data.

To incorporate the different scenarios mentioned within the development of the demonstrator, nested `IF` and `IF ELSE` statements is needed. Figure 5.10 shows a schematic overview of the different scenarios that can take place within the time a customer is visiting a store

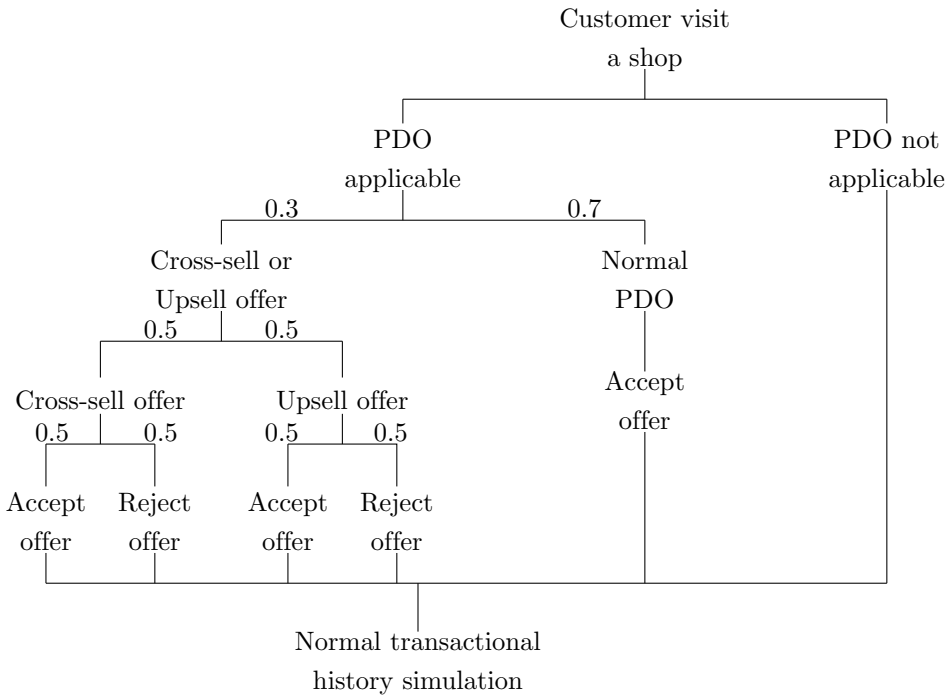


Figure 5.10: Schematic overview of different PDO scenarios

given the values drawn from the respective distributions.

To determine a suitable analysis approach to be used in the PDO predictor, a comparison of the different analysis approaches using different input scenarios is presented next.

5.2.3 Comparison and evaluation of NPD-analysis approaches for the PDO predictor

This subsection provides a comparison and evaluation of the analysis approaches identified in Subsection 5.2.1. It was evident in Subsection 5.2.1.2 that the WAA outperformed the AAA. Therefore the AAA approach is not included in this comparison and evaluation.

5.2.3.1 Key performance indicators for the comparison and evaluation

The analysis approaches will be evaluated based on two key performance indicators (KPIs). The first KPI is the *mean absolute difference in days* between the NPD predicted and the actual purchase date of the product. This was already seen in the preliminary experiments in Subsections 5.2.1.1 and 5.2.1.2. This value must be as small as possible, therefore minimum values from the analysis approaches will be considered best.

In order to propose a PDO, the customer must enter any participating outlet within a given time range of the NPD predicted for the specific product. The WAA and RCAA will be

evaluated at various time ranges to identify the most appropriate time range that customers can be proposed PDOs. The second KPI is therefore the *number of times a NPD is predicted correctly given a certain time range*. This will be expressed as a percentage of the total number of PDO predictions for a given customer-product pair.

5.2.3.2 Comparison and evaluation between the WAA and the RCAA

This subsection investigates the comparison and evaluation of the two analysis approaches identified in 5.2.1. An evaluation dataset was generated by the simulator explained in Chapter 4 to contain pseudo-customer data with purchasing behaviour not influenced by any promotional strategies. The dataset contained 5 000 customers and was simulated for a three year time period. The researcher used both the WAA and the RCAA to predict the NPD and evaluated if the prediction was accurate based on the time the customer actually purchased the specific product again.

For the RCAA the mean absolute difference is evaluated at different repurchase probabilities where the probabilities ranged from 0.6 to 0.9 and were incremented by 0.1 each time.

The time range for which a PDO is applicable for a customer based on the NPD was varied from two to five days for both the WAA and the RCAA. The researcher evaluated the different ranges at different repurchase probabilities for the RCAA as done with the first KPI.

Table 5.4: KPI 1: WAA and RCAA mean absolute difference in days

Analysis Approach	**Repurchase Probability**	**Mean absolute difference (days)**
WAA	–	2.4431
RCAA	**0.6**	2.4768
	0.7	2.6956
	0.8	3.1175
	0.9	3.7816

The first KPI results can be seen in Table 5.4. The mean absolute difference is the difference in days between the NPD predicted and the actual purchase date and thus the range within which a PDO is valid does not have an effect on this KPI and for this reason is not included in Table 5.4. The WAA does not use repurchase probabilities in the prediction of the NPD, therefore the WAA only has one mean absolute difference which was 2.4431 days for the evaluation dataset. The RCAA was evaluated at each repurchase probability specified.

Table 5.4 illustrated that repurchase probability increases when mean absolute difference in days increases. This is a consequence from the fact that if the repurchase probability is

higher, the number of days between purchases is smaller and the NPD is actually predicted too early and thus misses the opportunity of the PDO because the customer did not want to buy the product yet or have not been to a participating retail outlet yet. The customer buys the product again after the NPD that was predicted. For this reason the mean absolute difference is larger when the repurchase probability is higher.

Table 5.5: KPI 2: WAA and RCAA accuracy

Range	**WAA**	**RCAA**			
		Repurchase Probability			
	–	**0.6**	**0.7**	**0.8**	**0.9**
2	57.15%	56.72%	53.54%	47.14%	37.54%
3	65.23%	72.84%	69.60%	62.81%	51.65%
4	85.27%	84.82%	81.56%	74.86%	64.27%
5	93.23%	92.75%	89.62%	83.82%	74.96%

The second KPI results can be seen in Table 5.5. The accuracy of the NPD predictions is calculated as the number of PDOs that were predicted correctly within range of the NPD from the total number of times the customer would be expected to buy the product periodically. The WAA was evaluated by varying the ranges from two to five days.

The same was done with the RCAA but it was also evaluated by varying the repurchase probabilities from 0.6 to 0.9. It is expected that the accuracy of NPD predictions will increase when the time range increases since this allows for a bigger time frame to propose PDOs to a customer. From the RCAA accuracies displayed in Table 5.5 one can see that the accuracy also decreases as the repurchase probability increases at a given time period. This is expected as the mean absolute difference is larger at a higher repurchase probability.

By comparing the WAA and the RCAA it is clear that the WAA is superior to the RCAA at a repurchase probability of 0.9 at all ranges. However, when compared at 0.6 and all ranges the two approaches seem to perform similar.

This led to the researcher investigating the possibility of combining the two approaches by using the weighted average number of days between purchases to create the repurchase curves for the customer-product pairs. This is discussed in the following subsection.

5.2.3.3 Comparison and evaluation between the RCAA and the WRCAA

For this, the same evaluation dataset was used and (5.6) was used to draw the repurchase curve instead of $\triangle T_i$ in Subsection 5.2.1.3. The method of creating the repurchase curve stayed the same as in Subsection 5.2.1.3 and the NPD was calculated using (5.7). Both the

KPIs were computed for this approach which is referred to as the *weighted repurchase curve analysis approach* (WRCAA) and was compared to the RCAA.

Table 5.6: KPI 1: RCAA and WRCAA mean absolute difference in days

Probability	**Analysis Approach**	
	RCAA	**WRCAA**
0.6	2.4768	2.3233
0.7	2.6956	2.3281
0.8	3.1175	2.3392
0.9	3.7816	2.3639

Investigating the first KPI in Table 5.6, the WRCAA provided more or less the same mean absolute difference in days for the various repurchase probabilities. These values are also smaller than those of the RCAA and the WAA and thus confirm that by combining the WAA and the RCAA, improved answers can be expected.

By examining the WRCAA values for all repurchase probabilities in Table 5.6 one would ask the question if the repurchase probabilities have a significant influence since the mean absolute difference values have minor variations. This can be explained by identifying the repurchase curves for a specific customer-product-pair.

Repurchase curves for the specific customer-product pair were drawn using the evaluation dataset and for various time lengths starting at six months and incremented with six months until the three year time period was reached. Figure 5.11 and Figure 5.12 illustrates the different repurchase curves for various time lengths for both analysis approaches.

The RCAA curves in Figure 5.11 have a wider range of days between purchases than the WRCAA in Figure 5.12. The x-axis values extracted from the graphs in Figure 5.12 at the different probabilities are within a two day range from one another. The x values are rounded to obtain integer values as the prediction does not work in fraction of days.

This is a consequence of using the weighted average in the WRCAA and results in the mean absolute difference in days being similar at all repurchase probabilities for the WRCAA shown in Table 5.6. It is also clear in both Figure 5.11 and Figure 5.12 the repurchase curves improve for both approaches over time.

The accuracy is increased by using the WRCAA and is displayed in Table 5.7 at the various ranges and repurchase probabilities. As expected and also seen in the comparison between the WAA and RCAA, the accuracy increases as the range increases. The accuracies do not differ as much for the various repurchase probabilities at a given time range following the same argument as with the first KPI comparing the RCAA and the WRCAA.

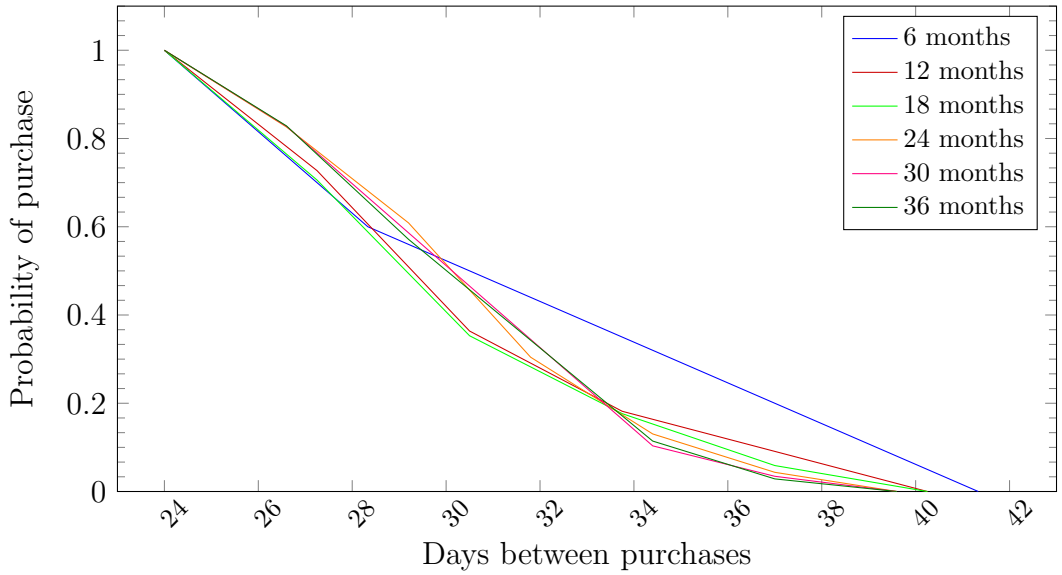


Figure 5.11: Repurchase curves using RCAA at different time lengths

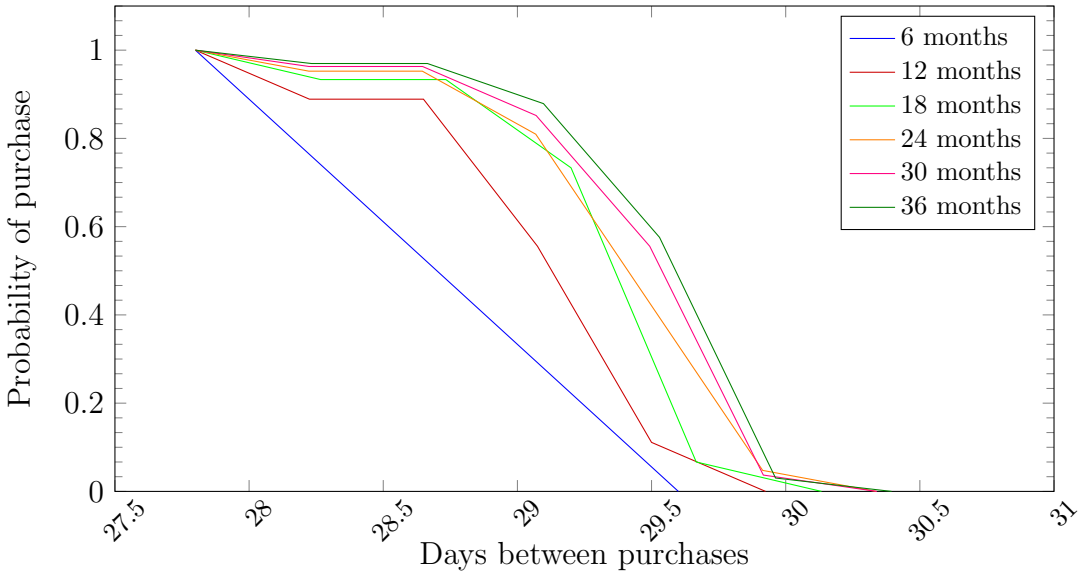


Figure 5.12: Repurchase curves using WRCAA at different time lengths

After conducting this comparison and evaluation a conclusion could be made that the WRCAA provided more accurate answers when compared to the RCAA at a higher repurchase probability, but also the WRCAA preformed similar to the RCAA at a lower repurchase probability which was similar to the WAA. The accuracies are also dependent on the range chosen and the researcher cannot disclose which is superior as the minimum accuracy to be obtained is subjective to the enterprise providing this service. For this reason the comparison between the RCAA and the WRCAA at the various time ranges and repurchase probabilities led to having 32 test scenarios and will be tested with the PDO demonstrator in Chapter 6.

Table 5.7: KPI 2: RCAA and WRCAA accuracy

Analysis Approach	Range	Repurchase Probability			
		0.6	0.7	0.8	0.9
RCAA	2	56.72%	53.54%	47.14%	37.54%
	3	72.84%	69.60%	62.81%	51.65%
	4	84.82%	81.56%	74.86%	64.27%
	5	92.75%	89.62%	83.82%	74.96%
WRCAA	2	59.36%	59.29%	59.13%	58.76%
	3	75.50%	75.43%	75.26%	74.92%
	4	87.31%	87.23%	87.06%	86.69%
	5	94.77%	94.70%	94.54%	94.18%

The following section elucidate the development of the PDO demonstrator and will be developed to incorporate both the RCAA and the WRCAA for the PDO predictor.

5.3 Development of the PDO demonstrator

The previous section shed light on theoretical aspects used in the design of the PDO demonstrator. This section will initiate the technical development of the PDO demonstrator using Matlab. The PDO demonstrator uses some of the functionalities of the simulator to generate customer purchases for each day along with the PDO predictor which identifies PDOs to be proposed to customers.

The design of the PDO demonstrator was the subject of discussion in Subsection 5.2.2 and two analysis approaches were identified in Subsection 5.2.3 to be used in the PDO demonstrator. Both these analysis approaches required functions to update the customer-product pairs' repurchase curves and thus the next purchase dates. Algorithm 1 represents the function where the NPD is predicted using the RCAA. Whereas, Algorithm 2 utilises the WRCAA to predicted the NPD of the customer-product pairs.

The PDO predictor is designed to analyse the historic data before any PDOs are generated. Thereafter, the PDO demonstrator continues emulating the real world process of customer purchases as done by the simulator, but the PDO demonstrator also uses the analysed data to propose PDOs to customers. For each month of purchases generated the PDO demonstrator must:

1. Determine the same data elements as described in Subsection 4.3.4. These elements are:

Algorithm 1 NPD function: Repurchase curve analysis approach

```
Begin
Input: Freq, NPD, LastQty and LP
If Freq is equal or larger than four
    Calculate NPD using RCAA for customer-product pair Else
        If Freq is equal or larger than one
            Record time between purchases Else
            Record △T_i of customer-product pair
        End
End
```

Algorithm 2 NPD function: Weighted repurchase curve analysis approach

```
Begin
Input: Freq, NPD, LastQty and LP
If Freq is equal or larger than four
    Calculate NPD using WRCAA for customer-product pair Else
        If Freq is equal or larger than one
            Record time between purchases Else
            Record △T_i of customer-product pair
        End
End
```

- the respective customers who visit the stores on certain days within a month,
- the respective store each customer visits,
- the time a customer visits a store, and
- to update customers' last purchase date(s).

2. Determine whether or not PDOs are applicable to the respective customers by using the PDO predictor

3. If PDOs are applicable, determine whether it will be a normal PDO or a cross-sell or upsell PDO

4. If cross-sell or upsell PDOs are presented, the customer accepts or rejects it

5. Generate transactional history as described in Subsection 4.3.8

Algorithm 3 describes the working of the PDO demonstrator incorporating the PDO predictor and the NPD functions in Algorithm 1 and 2.

Algorithm 3 PDO Demonstrator

Begin
Set `current date`
Set SQL table IDs
Define `Freq, NPD, LastQty` and `LP` and set to zero
For $m = 1$ to the number of months
Initialise variables
Determine customer visits for month m
For $t = 1$ to number of days
  For customers visiting shops on day t
  Register purchase instance
  Update customer's last purchase date
  Set customer's base basket
    For all products with `Freq` larger than five
    Determine duration of product X NPD to current date
      If duration is smaller than or equal to range
      Generate normal PDO or cross- sell and upsell probability
      Generate accept or reject probability
      CASE #1: Normal PDO
        Generate discount
        Record PDO
        Set PDO `Status` as 1
        Record transaction
        Update product next purchase date and stock on hand
      End CASE #1

```
25:          CASE #2: Cross-sell or Upsell PDO
26:          Generate cross-sell or upsell probability
27:            CASE #2.1: Cross-sell PDO
28:              Select other product from cross-sell matrix
29:              Record PDO
30:              If Reject
31:              Set PDO Status as 0 Else
32:              Set PDO Status as 1
33:              Record transaction
34:              Update product next purchase date and stock on hand
35:            End CASE #2.1
36:            CASE #2.2: Upsell PDO
37:              Select other product from upsell matrix
38:              Record PDO
39:              If no other product exists exit loop Else
40:              If Reject
41:              Set PDO Status as 0 Else
42:              Set PDO Status as 1
43:              Record transaction for product
44:              Remove product X from base basket
45:              Update product next purchase date and stock on hand
46:            End CASE #2.2
47:          End CASE #2
48:        Select products for transactional history
49:        Record transaction for products selected
50:        Update product next purchase date and stock on hand
51:        Next customer for day t
52:    Write tables to SQL database
53:    Clear tables
54:    Assign current date to next date
55:  Next t
56:  Next m
```

The NPDs are updated each time a product is bought. Algorithm 3 also illustrates the different cases where the PDO predictor predicts a PDO and the PDO demonstrator proposes the different types of PDOs: normal, cross-sell and upsell. The demonstrator will be executed using each of the NPD functions. The following section discusses the event when a new customer enters the system.

5.4 New customer entering the system

This section discusses the event when a new customer enters the system. Since the new customer has no historical transactional data, the system will use machine learning techniques to place the new customer in a customer segment. Customer segmentation is explained in Section 2.5.

When a new customer signs up for this service of personalised discount offers they are prompted to enter preferences from a list. A minimum of one preference entry is required to complete this process. The new customer is allocated to a customer segment based on the preferences and purchasing behaviour of customers within that segment.

This process is done in two steps:

1. Cluster customers based on RFM values.

2. Decision rules for allocating new customers to clusters.

The existing customers are clustered based on their transactional history using the RFM analysis explained in Subsection 2.6.1 using a 5-score analysis.

For each RFM indicator a minimum and maximum value are determined and the indicators are divided into five equal classes using (5.8) as the class size for each RFM indicator individually.

$$\text{Indicator\_class\_size} = \frac{\text{Indicator\_max} - \text{Indicator\_min}}{5} \tag{5.8}$$

Customers are allocated R, F and M values based on the class they belong to based on each individual RFM indicator. After the R, F and M value for each customer is assigned, the k–means clustering algorithm is utilised to divide the customers into clusters based on their R, F and M values. The k–means clustering algorithm was identified as an unsupervised machine learning technique in Table 2.20 and is a commonly used algorithm for clustering.

An example dataset is used for the practical and visual explanation of this section. Figure 5.13 explains the classes of each RFM indicator. The recency parameter is measured on the `LastPurchase` attribute of each customer. The earliest last purchase date (Indicator_min) is the start date of the recency parameter (lowest recency) and the latest last purchase date

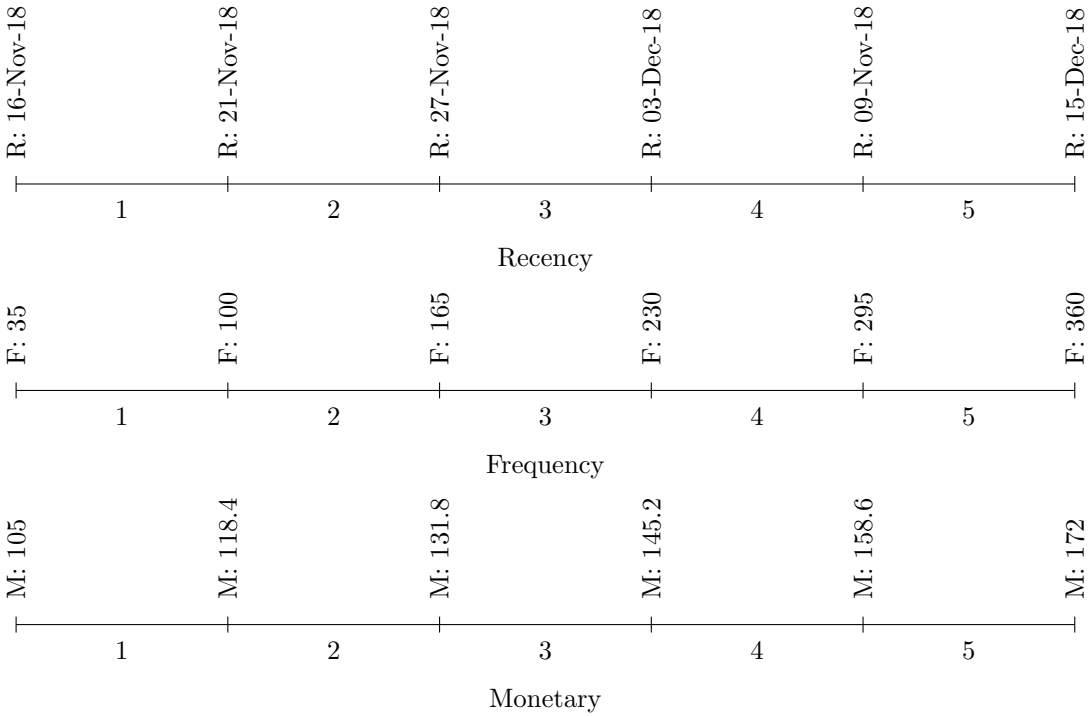


Figure 5.13: RFM classes for example dataset

(Indicator_max) is the end date of the recency parameter (most recent). Referring to Figure 5.13 customers are divided into five classes of equal size between the start and end date of the recency parameter based on their last purchase date. The associated class number is the specific customer's recency value. For example if a customer's last purchase date was 25-Nov-18, their recency value would be two.

The frequency parameter is measured on the number of visits to participating outlets. As with recency, the customer with the lowest frequency (Indicator_min) represents the start of the frequency parameter and the customer with the highest frequency (Indicator_max) represents the end of the frequency parameter. So for this example if a customer has a frequency of 190 then they would have a frequency class value of three.

For the last parameter, monetary, the total amount spent by a customer is used. The customer with the lowest total amount spent (Indicator_min) represents the start of the monetary parameter and the customer with the highest total amount spent (Indicator_max) represents the end of the monetary parameter. For example if a customer spent a total amount of R150 then they would have a monetary value of four referring to the classes shown in Table 5.13.

After identifying the RFM values of customers it is necessary to identify the number of clusters to be used within the k-means clustering algorithm. The researcher used the built-in Matlab function *"evalcluster"*. This function provides the option to choose the algorithm with which it should evaluate the number of clusters. In this case it is the k-means algorithm. The

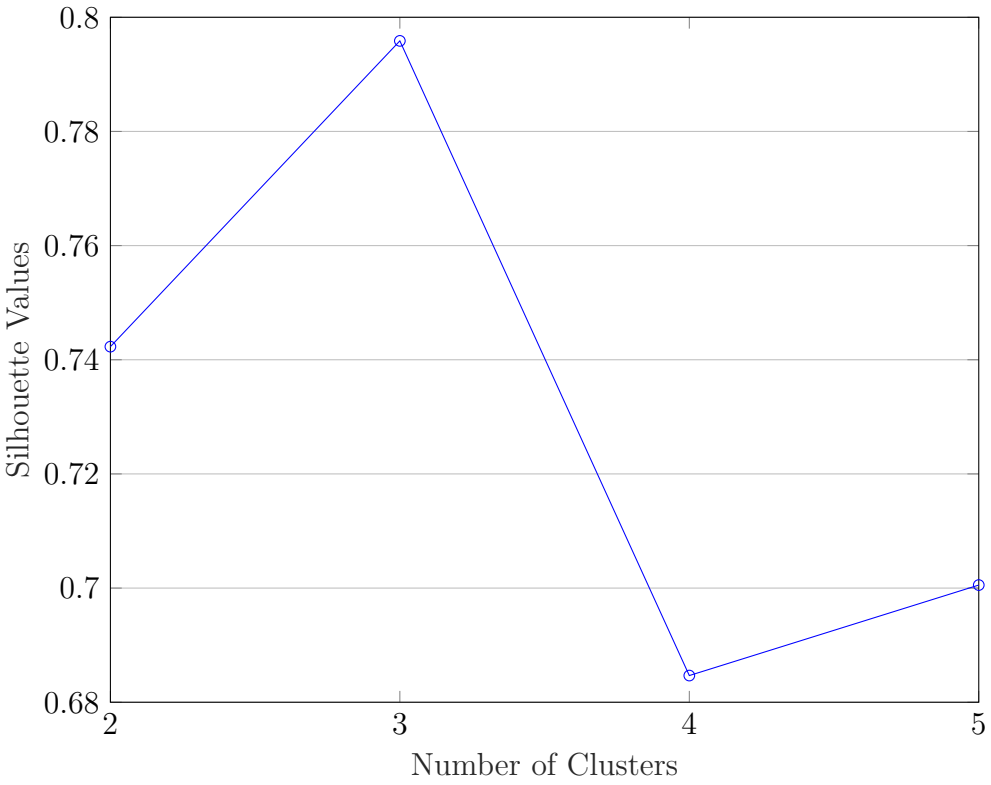


Figure 5.14: Silhouette plot for evaluating the number of clusters

function also includes a clustering evaluation criterion which was selected as the silhouette criterion which provides silhouette values for the number of clusters identified.

Figure 5.14 illustrates the silhouette values identified by the built-in Matlab function. The optimal number of clusters is chosen where number of clusters that provides the highest silhouette value.

In this example the optimal number of clusters is three. This number is now used in the k-means clustering algorithm which is also available in Matlab as a built-in function. Figure 5.15 illustrates the cluster assignments done by the k-means algorithm. Each customer is now assigned to a cluster based on their R, F and M values.

Everything up to this point forms part of step one, the following part is done in order to create rules by which the new customers can be assigned to an appropriate cluster having similar preferences as customers within that cluster. In order to create these rules, decision trees, which were identified in Table 2.19 as a classification technique, are utilised.

Lakshmi Prasad (2016) identifies decision trees as a powerful method for classification, prediction and facilitating decision-making in sequential decision problems. According to Trewartha (2006), using decision trees in conjunction with other data mining tools provides an almost complete implementation of the data mining process. The researcher decided to use decision trees, because the output of a decision tree is provided in a form of decision rules

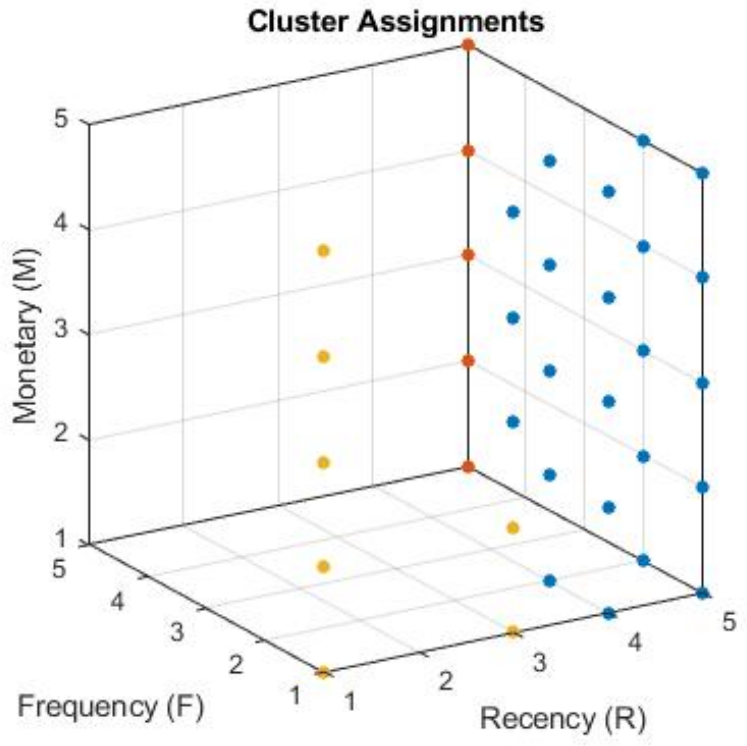


Figure 5.15: Cluster assignments for example dataset based on RFM values

which is required for allocating a new customer to a cluster.

Continuing to use this example dataset, a table is constructed with the maximum number of preferences as columns and an additional column including the cluster number. The row indices represent each customer. A *"Yes"* or *"No"* is entered in the columns that represent the preferences of that specific customer. This table is used within the decision tree algorithm to create decision rules which will help to assign an appropriate cluster to a new customer.

Decision trees classify specific entities into distinct classes based on features of the entities. A root is followed by internal nodes and each node is labelled with a question and an arc associated with each node covers all the possible responses (Ngai et al., 2009). In the event of allocating a new customer to an appropriate cluster, the internal nodes are labelled with the question: *"Did the new customer choose Preference X ?"*. The node is branched into a *"Yes"* or *"No"* response and this is done until all questions are covered and a cluster number is allocated.

The rules created for the example dataset are listed in Table 5.8. From these rules a new customer can be allocated to a specific cluster based on the preferences they entered. So for example if a new customer enters the system and submits Preference 1 and Preference 3 they

will be assigned to cluster one.

Table 5.8: Decision rules of example data

Rules	Rule description
Rule 1:	**IF** Pref4 = No **AND** Pref2 = No **AND** Pref3 = No **AND** Pref5 = No **THEN** clusternr = 3
Rule 2:	**IF** Pref4 = No **AND** Pref2 = No **AND** Pref3 = No **AND** Pref5 = Yes **AND** Pref1= No **THEN** clusternr = 3
Rule 3:	**IF** Pref4 = No **AND** Pref2 = No **AND** Pref3 = No **AND** Pref5 = Yes **AND** Pref1= Yes **THEN** clusternr = 2
Rule 4:	**IF** Pref4 = No **AND** Pref2 = No **AND** Pref3 = Yes **AND** Pref5 = No **AND** Pref1= No **THEN** clusternr = 2
Rule 5:	**IF** Pref4 = No **AND** Pref2 = No **AND** Pref3 = Yes **AND** Pref5 = No **AND** Pref1= Yes **THEN** clusternr = 1
Rule 6:	**IF** Pref4 = No **AND** Pref2 = No **AND** Pref3 = Yes **AND** Pref5 = Yes **THEN** clusternr = 1
Rule 7:	**IF** Pref4 = No **AND** Pref2 = Yes **AND** Pref1 = No **AND** Pref3 = No **AND** Pref5= No **THEN** clusternr = 1
Rule 8:	**IF** Pref4 = No **AND** Pref2 = Yes **AND** Pref1 = No **AND** Pref3 = No **AND** Pref5= Yes **THEN** clusternr = 2
Rule 9:	**IF** Pref4 = No **AND** Pref2 = Yes **AND** Pref1 = No **AND** Pref3 = Yes **THEN** clusternr = 1
Rule 10:	**IF** Pref4 = No **AND** Pref2 = Yes **AND** Pref1 = Yes **AND** Pref3 = No **THEN** clusternr = 2
Rule 11:	**IF** Pref4 = No **AND** Pref2 = Yes **AND** Pref1 = Yes **AND** Pref3 = Yes **AND** Pref5 = No **THEN** clusternr = 2
Rule 12:	**IF** Pref4 = No **AND** Pref2 = Yes **AND** Pref1 = Yes **AND** Pref3 = Yes **AND** Pref5 = Yes **THEN** clusternr = 3
Rule 13:	**IF** Pref4 = Yes **AND** Pref3 = No **AND** Pref2 = No **AND** Pref1 = No **AND** Pref5 = No **THEN** clusternr = 3
Rule 14:	**IF** Pref4 = Yes **AND** Pref3 = No **AND** Pref2 = No **AND** Pref1 = No **AND** Pref5 = Yes **THEN** clusternr = 1
Rule 15:	**IF** Pref4 = Yes **AND** Pref3 = No **AND** Pref2 = No **AND** Pref1 = Yes **THEN** clusternr = 1
Continued on next page	

Table 5.8 continued

Rules	Rule description
Rule 16:	**IF** Pref4 = Yes **AND** Pref3 = No **AND** Pref2 = Yes **AND** Pref5= No **THEN** clusternr = 3
Rule 17:	**IF** Pref4 = Yes **AND** Pref3 = No **AND** Pref2 = Yes **AND** Pref5= Yes **AND** Pref1= No **THEN** clusternr = 2
Rule 18:	**IF** Pref4 = Yes **AND** Pref3 = No **AND** Pref2 = Yes **AND** Pref5= Yes **AND** Pref1= Yes **THEN** clusternr = 3
Rule 19:	**IF** Pref4 = Yes **AND** Pref3 = Yes **AND** Pref2 = No **AND** Pref5= No **THEN** clusternr = 2
Rule 20:	**IF** Pref4 = Yes **AND** Pref3 = Yes **AND** Pref2 = No **AND** Pref5= Yes **THEN** clusternr = 3
Rule 21:	**IF** Pref4 = Yes **AND** Pref3 = Yes **AND** Pref2 = Yes **AND** Pref5= No **AND** Pref1= No **THEN** clusternr = 1
Rule 22:	**IF** Pref4 = Yes **AND** Pref3 = Yes **AND** Pref2 = Yes **AND** Pref5= No **AND** Pref1= Yes **THEN** clusternr = 3
Rule 23:	**IF** Pref4 = Yes **AND** Pref3 = Yes **AND** Pref2 = Yes **AND** Pref5= Yes **AND** Pref1= No **THEN** clusternr = 3
Rule 24:	**IF** Pref4 = Yes **AND** Pref3 = Yes **AND** Pref2 = Yes **AND** Pref5= Yes **AND** Pref1= Yes **THEN** clusternr = 1

This section shed light on the event when a new customer enters the system and will be used to provide promotional offers to a new customer based on the buying behaviour of customers with similar preferences.

5.5 Chapter 5 summary

In this chapter, the design and development of the PDO demonstrator were presented. The PDO demonstrator is used to propose personalised discount offers to customers based on their transactional history. The demonstrator also contains functionalities of the simulator to continue imitating the real-world purchasing process.

The researcher investigated different analysis approaches to identify the NPD. First, the AAA and WAA were compared including and excluding quantity where after the RCAA was discussed. The PDO predictor would use the NPD-analysis approach and thus the PDO predictor design showed how PDO would be identified. This also included cross-sell and upsell

offers.

The WAA and RCAA were compared and evaluated using an evaluation dataset generated by the simulator. The approaches were evaluated based on two KPIs identified in this chapter. The WAA and RCAA were combined to create the WRCAA and the latter was compared to the RCAA based on the two KPIs. This comparison and evaluation led to developing the PDO demonstrator by including both the RCAA and WRCAA. This chapter also contains the pseudocode for the PDO demonstrator.

Lastly, the event when a new customer enters the system was also investigated and decision rules were generated to allocate the new customer to an appropriate cluster based on preferences similar to other existing customers.

The results obtained from the PDO demonstrator along with a discussion thereof will be presented in the following chapter.

Chapter 6

Experiments and results

The previous chapter explained the PDO demonstrator design and development along with a comparison and evaluation of various analysis approaches. This chapter will discuss the experiments and results that were obtained by executing the experiments with the PDO demonstrator. The methodology followed will initiate this chapter.

6.1 Methodology for experiments and results

This chapter initiates the fourth and final phase identified by the research methodology in Section 1.5. The researcher must execute the 32 scenarios identified in Chapter 5 using the PDO demonstrator. The scenarios must be evaluated for both KPIs identified in Subsection 5.2.3 utilising both the RCAA and WRCAA in the PDO demonstrator. The results of the experiments must be discussed and the researcher must provide a customer journey example for a chosen repurchase probability and time range.

6.2 Comparison and evaluation of results obtained from PDO demonstrator

The evaluation and comparison conducted in Subsection 5.2.3 used an evaluation dataset that was simulated using the simulator designed in Chapter 4 before the evaluation and comparison commenced. The evaluation dataset did not contain any promotional influences and was used to test the various NPD-analysis approaches.

This section will display the results obtained by evaluating the PDO demonstrator with the 32 scenarios when promotional efforts are introduced. These promotional influences are introduced by the personalised discount offers (PDOs). The PDO demonstrator will continuously emulate the real-world process of customer purchases along with introducing promotional efforts identified by the PDO predictor. If a PDO is identified, the PDO demonstrator can propose it as a normal PDO, cross-sell PDO or upsell PDO. These promotional efforts will affect the customers' normal purchasing behaviour. The capability of predicting accurate NPDs by the PDO predictor must be evaluated when promotional influences are present.

The mean absolute difference in days between the NPD predicted and the actual purchase date is presented in Table 6.1 for the various repurchase probabilities and ranges. The values are similar for both the RCAA and the WRCAA at the different repurchase probabilities and

Table 6.1: KPI 1: PDO demonstrator mean absolute difference in days utilising RCAA and WRCAA

Analysis Approach	Range	Repurchase Probability			
		0.6	0.7	0.8	0.9
RCAA	2	3.4377	3.4322	3.3579	3.8030
	3	3.5063	3.3572	3.2783	3.3438
	4	3.5049	3.3127	3.2216	3.3396
	5	3.4691	3.2605	3.1897	3.3334
WRCAA	2	3.3350	3.3176	3.3127	3.3191
	3	3.4155	3.4019	3.4014	3.4140
	4	3.5185	3.5167	3.5581	3.5274
	5	3.6546	3.6480	3.6371	3.6467

time ranges. In 5.6 the repurchase probabilities were not included because the evaluation was done on a dataset already containing simulated purchases.

During this evaluation the PDO demonstrator continued to create customer purchases for the different scenarios and thus the purchases were not exactly the same. Therefore, variations in the mean absolute difference in days were present. Comparing Table 5.6 and Table 6.1 the mean absolute difference in days differ in the range of one day for the WRCAA and the RCAA performed the same as in the scenario where the repurchase probability was 0.9 but no promotional efforts were introduced in Subsection 5.2.3. The mean absolute difference in days for the 32 scenarios are within the maximum range of five days and this shows that the PDO predictor can predict the NPD to propose PDOs when promotional efforts are introduced.

Table 6.2 presents the number of times a NPD is predicted correctly given a certain time range. As expected the accuracies increase as the time ranges increase, but the accuracies did decrease when promotional efforts were introduced by the PDO demonstrator. It is interesting to see that even though accuracies decreased, the lowest accuracy in Table 6.2 is still higher than the lowest accuracy in Table 5.7.

From this comparison and evaluation a conclusion was made that the two analysis approaches investigated performed similar, but it was comfirmed that the PDO predictor was capable of predicting the NPD to be proposed as PDOs by the PDO demonstrator when promotional efforts are introduced.

The following two sections illustrate the PDO demonstrator utilising the RCAA and the WRCAA, respectively. Each section contains an example of an individual customer journey using this service.

Table 6.2: KPI 2: PDO demonstrator accuracy utilising RCAA and WRCAA

Analysis Approach	Range	Repurchase Probability			
		0.6	0.7	0.8	0.9
RCAA	2	41.94%	41.94%	43.07%	42.57%
	3	52.33%	57.18%	58.78%	56.98%
	4	66.53%	70.08%	71.20%	68.94%
	5	77.57%	80.27%	81.24%	79.08%
WRCAA	2	43.76%	44.15%	44.31%	44.22%
	3	56.27%	56.57%	56.50%	56.40%
	4	66.18%	66.23%	65.37%	65.92%
	5	74.11%	74.12%	74.08%	73.94%

6.3 PDO demonstrator example employing the RCAA

This section illustrates the working of the PDO demonstrator when the PDO predictor is set to use the RCAA explained in Subsection 5.2.1.3 for NPD predictions and for this example the researcher chose the repurchase probability at 0.7 and the time range at three days. The simulator designed in Chapter 4 forms part of the PDO demonstrator and was used to generated pseudo-customer data containing customer purchasing behaviour until the point in simulation time when the PDO predictor conditions are met. When the PDO demonstrator starts proposing PDOs, it continues to emulate the real world process of creating customer purchases as done by the simulator. These records include the cross-sell and upsell instances.

For this specific example the PDO demonstrator created approximately 600 000 instances of customers purchasing products at various stores. The purchasing instances were recorded as orders within the Orders table. The orders resulted in approximately 10 317 000 transactional history records. These records represent the individual products bought during each order and were recorded in the Transactional History table. Approximately 7 722 000 PDOs were proposed to customers, of which 85.8% were accepted and 14.2% were rejected. This verifies the development of the demonstrator as it was designed having a 50% acceptance and rejection rate for cross-sell and upsell PDOs and a 100% acceptance rate for normal PDOs. These values will differ in practice since they are based on customer decision-making.

Looking at the approximately 6 625 000 PDOs accepted, the number of normal PDOs proposed and thus also accepted was approximately 5 527 000, whereas the cross-sell PDOs accepted were 593 000 and the upsell PDOs 504 000. Table 6.3 illustrates this result. The PDO demonstrator was designed having a cross-sell and upsell opportunity of 30% and 70% normal

PDOs. The result from Table 6.3 verifies that the demonstrator was developed correctly.

Table 6.3: Percentages of different PDOs accepted by all customers using the RCAA in the PDO demonstrator

Normal PDOs	Cross-sell PDOs	Upsell PDOs
83.43%	8.95%	7.61%

In order to illustrate the process of proposing PDOs to customers, the example of Customer M will continue in the following subsection.

6.3.1 Customer journey example employing the RCAA

This subsection investigates Customer M's purchasing behaviour towards Product 133 when the PDO predictor is set to use the RCAA for NPD predictions and for this example the researcher chose the repurchase probability at 0.7 and the time range at three days. Customer M had 24 order instances which resulted in 1 003 transactional history records being recorded. Customer M received 615 PDOs of which 545 were accepted and 70 were rejected. Table 6.4 represents the combination of different PDOs accepted by Customer M.

Table 6.4: Percentages of different PDOs accepted by Customer M using the RCAA

Normal PDOs	Cross-sell PDOs	Upsell PDOs
83.30%	7.89%	8.81%

PDOs for Product 133 were proposed to Customer M based on the transactional history of the customer. The PDO demonstrator also continued to generate normal purchases of Product 133 by Customer M. The results are provided in Table 6.5.

Table 6.5: Transactional history of Customer M's Product 133 using the RCAA

Purchase instance	**Purchase date**	**Offered as PDO**	**Accepted/ Rejected**	**PDO type**	**Expected NPD**	**PDO product**
1	19-Jan-16	No	–	–	–	–
2	17-Feb-16	No	–	–	–	–
3	15-Mar-16	No	–	–	–	–
4	19-Apr-16	No	–	–	–	–
5	14-May-16	No	–	–	14-Jun-16	–
6	16-Jun-16	Yes	Accepted	Normal PDO	15-Jul-16	133
7	15-Jul-16	Yes	Accepted	Normal PDO	12-Aug-16	133
–	15-Aug-16	Yes	Accepted	Upsell PDO	12-Aug-16	133 to 102
8	14-Sep-16	No	–	–	13-Oct-16	–
9	14-Oct-16	Yes	Accepted	Normal PDO	12-Nov-16	133
10	14-Nov-16	No	–	Cross-sell PDO	13-Dec-16	133 with 166
11	12-Dec-16	No	–	Cross-sell PDO	10-Jan-17	133 with 115
12	12-Jan-17	Yes	Accepted	Normal PDO	09-Feb-17	133
13	12-Feb-17	Yes	Accepted	Normal PDO	12-Mar-17	133
14	15-Mar-17	Yes	Accepted	Normal PDO	12-Apr-17	133
15	13-Apr-17	Yes	Accepted	Normal PDO	11-May-17	133
16	10-May-17	No	–	Upsell PDO	07-Jun-17	133 to 102
17	10-Jun-17	Yes	Accepted	Normal PDO	08-Jul-17	133

Continued on next page

Table 6.5 continued

Purchase instance	Purchase date	Offered as PDO	Accepted/ Rejected	PDO type	Expected NPD	PDO product
18	12-Jul-17	No	–	–	09-Aug-17	–
19	07-Aug-17	Yes	Accepted	Normal PDO	04-Sep-17	133
20	08-Sep-17	No	–	–	06-Oct-17	–
21	07-Oct-17	Yes	Accepted	Normal PDO	04-Nov-17	133
22	10-Nov-17	No	–	–	08-Dec-17	–
23	07-Dec-17	Yes	Accepted	Normal PDO	14-Jan-18	133

From Table 6.5 purchase instances 1 to 5 represent the first five occasions where Customer M purchased Product 133. No PDOs are proposed within this time as the minimum frequency for the customer-product pair was not met yet. The minimum frequency was set to five as explained in Subsection 5.2.2. PDOs are only proposed after the minimum frequency is met and for this reason the first NPD prediction is only calculated at purchase instance five. The expected NPD is calculated and shown in column six and it was predicted that Customer M would purchase Product 133 again on 14-Jun-16.

Product 133 was purchased again on 16-Jun-16 at purchase instance 6 and because Product 133 was purchased within a three day range of the NPD predicted it was proposed and purchased as a normal PDO. This event occurred for purchase instance 7 and 9.

In the row between purchase instance 7 and 8 on 15-Aug-16 it was estimated that Customer M would be susceptible to buy Product 133 again. The PDO was presented as an upsell offer for Product 102 and Customer M accepted this offer. For this reason there is no purchase of Product 133 on this date in the row between purchase instance 7 and 8. Column three identifies that a PDO was offered and accepted and one can see in the last column of Table 6.5 that Product 102 was purchased as an upsell from Product 133. A customer does not buy the original product when an upsell is proposed so in this case Product 133 was not purchased and for this reason the expected NPD remained 12-Aug-16. The events where the PDO product column states *133 with x* represents the PDO of Product 133 being cross-sold to Product x and the case of an upsell the PDO product column indicates *133 to x*.

The upsell offer caused an interference in the periodical purchase pattern of Product 133 and Customer M purchased Product 133 as a normal purchase on 14-Sep-16 where after a new NPD was predicted for 13-Oct-16. On 14-Oct-16 Customer M purchased Product 133 as a normal PDO at purchase instance nine. At purchase instance 10 and 11, Product 133 was purchased but not with a PDO even though it was within a three day range of the NPD. Both of these times the PDO demonstrator identified Product 133 to be proposed as a PDO, but proposed it as a cross-sell offer. When a cross-sell offer is proposed the product from which the cross-sell originated must also be bought in order to qualify for the discount. Thus at purchase instance 10, Product 166 was purchased at a discount and Product 133 at the normal price. At purchase instance 11, Product 115 was presented as the cross-sell offer from Product 133. Customer M did not accept this offer, but still purchased product 133 at the normal price.

For instances 12 to 15, Product 133 was proposed as a normal PDO because it was within a three day range of the NPD predicted and thus also purchased at a discounted price. On 10-May-16 at purchase instance 16, Product 102 was proposed as an upsell offer based on the NPD of Product 133. The customer rejected this offer and purchased Product 133 at the normal price. Column three shows that Product 133 was thus not purchased due to a PDO.

At purchase instances 17, 19, 21 and 23 Product 133 was proposed as a normal PDO and also accepted. At purchase instances 18, 20 and 22 Product 133 were recorded as normal purchases because the purchase dates was not within a three day range of the predicted NPD. The difference between the purchase date and the predicted NPD was 4, 4 and 6 days for purchase instance 18, 20 and 22, respectively.

This section illustrates that the demonstrator is capable of proposing PDOs to customers based on their historical data using the RCAA. The next section will discuss the results of the demonstrator using WRCAA.

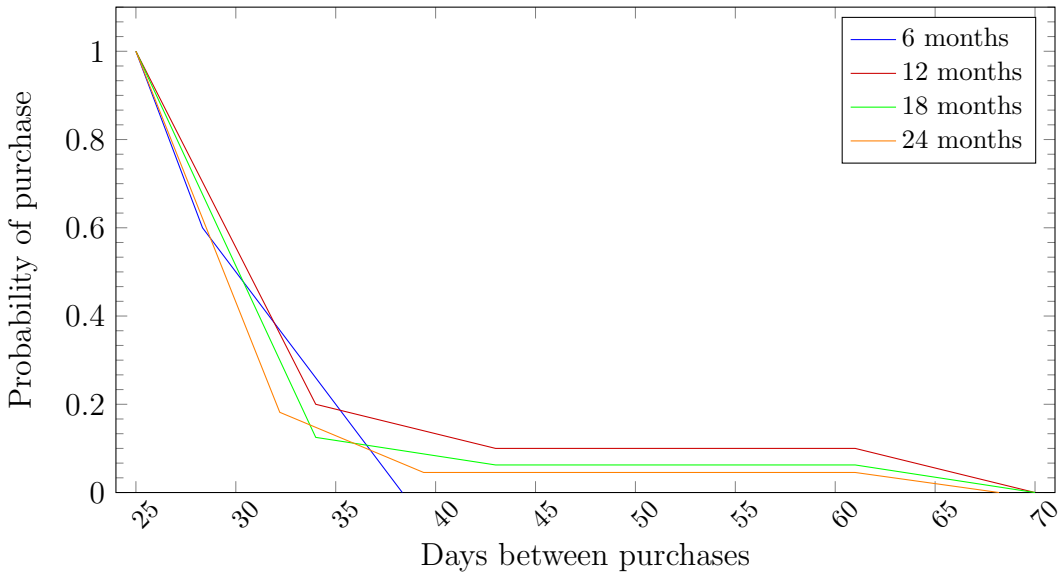


Figure 6.1: Repurchase curves using RCAA at different time lengths for Customer M's Product 133

In Figure 6.1 the repurchase curve for Customer M's Product 133 is presented for different time lengths. During the 12 month time period the interference of the upsell offer in the row between purchase instance 7 and 8 of Table 6.5 influenced the periodical purchase pattern and this influence can also be seen in the repurchase curves of the customer-product pair in Figure 6.1. It is clear to see that as time passes the repurchase curve improves as a result of more historical behaviour available.

6.4 PDO demonstrator example employing the WRCAA

This section illustrates the working of the PDO demonstrator, similar to the example in Section 6.3, but now the PDO predictor is set to use the WRCAA explained in Subsection

5.2.3.3 for NPD predictions. The researcher set the repurchase probability at 0.7 and the time range at three days for this example as well.

The PDO demonstrator created approximately 600 000 instances of customers purchasing products at various stores. The purchasing instances were recorded as orders within the Orders table and resulted in approximately 6 720 000 transactional history records represented in the Transactional History table. Approximately 3 673 000 PDOs were proposed to customers, of which 86.55% were accepted and 14.3% were rejected. This again verifies the development of the demonstrator as it was designed having a 50% acceptance and rejection rate for cross-sell and upsell PDOs and a 100% acceptance rate for normal PDOs.

From the approximately 3 148 000 PDOs accepted, the number of normal PDOs proposed and thus also accepted was approximately 2 623 000, whereas the cross-sell PDOs accepted were 281 000 and the upsell PDOs 243 000. Table 6.6 illustrates this result.

Table 6.6: Percentages of different PDOs accepted by all customers using the WRCAA in the PDO demonstrator

Normal PDOs	Cross-sell PDOs	Upsell PDOs
83.32%	8.94%	7.74%

In order to illustrate the process of proposing PDOs to customers using the WRCAA, the example of Customer M will be discussed in the following subsection.

6.4.1 Customer journey example employing the WRCAA

This subsection investigates Customer M's purchasing behaviour towards Product 133 when the PDO predictor uses the WRCAA for NPD predictions and for this example the researcher set the repurchase probability at 0.7 and the time range at three days. Customer M had 24 order instances which resulted in 1 010 transactional history records being recorded. Customer M received 657 PDOs of which 562 were accepted and 95 were rejected. Table 6.7 represents the combination of different PDOs accepted by Customer M.

Table 6.7: Percentages of different PDOs accepted by Customer M using the WRCAA

Normal PDOs	Cross-sell PDOs	Upsell PDOs
83.63%	8.90%	7.47%

Table 6.8 illustrates the PDOs proposed to Customer M for Product 133 based on the transactional history of the customer and along with the continued simulation of normal purchases of Product 133.

Table 6.8: Transactional history of Customer M's Product 133 using the WRCAA

Purchase instance	Purchase date	Offered as PDO	Accepted/ Rejected	PDO type	Expected NPD	PDO product
1	17-Jan-16	No	–	–	–	–
2	18-Feb-16	No	–	–	–	–
3	20-Mar-16	No	–	–	–	–
4	18-Apr-16	No	–	–	–	–
5	16-May-16	No	–	–	15-Jun-16	–
6	17-Jun-16	Yes	Accepted	Normal PDO	17-Jul-16	133
7	18-Jul-16	Yes	Accepted	Normal PDO	17-Aug-16	133
8	17-Aug-16	Yes	Accepted	Normal PDO	16-Sep-16	133
9	14-Sep-16	Yes	Accepted	Normal PDO	14-Oct-16	133
10	16-Oct-16	No	–	Upsell PDO	15-Nov-16	133 to 127
11	12-Nov-16	Yes	Accepted	Normal PDO	12-Dec-16	133
–	11-Dec-16	Yes	Accepted	Upsell PDO	12-Dec-16	133 to 155
12	13-Jan-17	No	–	–	12-Feb-17	–
13	11-Feb-17	No	–	Upsell PDO	13-Mar-17	133 to 150
–	10-Mar-17	Yes	Accepted	Upsell PDO	13-Mar-17	133 to 155
14	11-Apr-17	No	–	–	11-May-17	–
15	10-May-17	No	–	Upsell PDO	09-Jun-17	133 to 80
16	08-Jun-17	Yes	Accepted	Normal PDO	08-Jul-17	133

Continued on next page

Table 6.8 continued

Purchase instance	Purchase date	Offered as PDO	Accepted/ Rejected	PDO type	Expected NPD	PDO product
17	10-Jul-17	Yes	Accepted	Normal PDO	09-Aug-17	133
18	11-Aug-17	Yes	Accepted	Normal PDO	10-Sep-17	133
19	08-Sep-17	No	–	Cross-sell PDO	08-Oct-17	133 with 168
20	11-Oct-17	Yes	Accepted	Normal PDO	10-Nov-17	133
21	08-Nov-17	Yes	Accepted	Normal PDO	08-Dec-17	133
22	09-Dec-17	Yes	Accepted	Cross-sell PDO	08-Jan-18	133 with 115

In Table 6.8, purchase instance 1 to 5 represent the first five purchases of Product 133 by Customer M. The minimum frequency of a customer-product pair was set as five purchases. This must be met before PDOs can be proposed for the specific customer-product pair. At purchase instance 5 the first NPD is predicted on 15-Jun-16 for Product 133 purchased by Customer M.

At purchase instances 6 to 9 Product 133 was purchased within a three day range of the NPD predicted for each instance and was therefore proposed and purchased as normal PDOs. At purchase instance 10, the NPD predicted was in range of the purchase date of Product 133, but the product was not purchased as a PDO. This was the consequence of Product 127 proposed as an upsell offer from Product 133. Customer M rejected the upsell PDO and purchased Product 133 as a normal purchase at the normal price. On 12-Nov-16 at purchase instance 11 Product 133 was purchased as a normal PDO and the new NPD was predicted as 12-Dec-16. On 11-Dec-16, Customer M qualified for a PDO on Product 133, but this ofer was presented as an upsell offer for Product 155. Customer M accepted this upsell PDO and for this reason did not purchase Product 133 and therefore the row between purchase instance 11 and 12 no purchase of Product 133 was recorded and thus the NPD remained the same. The same event occurred again in the row between purchase instance 13 and 14.

At purchase instance 12 and 14 the purchase of Product 133 was recorded as normal purchases. This was a result of the previous acceptance of the upsell offers which caused interferences in the periodical purchase pattern of Product 133 by Customer M. At purchase instance 13, Customer M purchased Product 133 as a normal purchase even though the purchase date is within range of the NPD predicted. This case shows that the PDO was proposed as an upsell offer to Product 150, but was rejected and the customer purchased Product 133 at the normal price. The same event occurred at purchase instance 15, but the upsell offer was for Product 80.

Purchase instances 16 to 18, 20 and 22 all represent instances where Product 133 was purchased following a normal PDO because the purchase date was within a three day range from the NPD predicted. On 08-Sep-17, Product 133 was recorded as being purchased but not as a PDO even though the purchase date is within range of the NPD. A cross-sell offer was proposed for Product 168, but Customer M rejected this cross-sell offer and only bought Product 133. It is for this reason that the third column states that the product was not purchased as part of a PDO. At purchase instance 22 another cross-sell offer was presented for Product 133 with Product 115 and the customer accepted this offer. Product 115 was purchased at a discounted price because the customer purchased Product 133. Column 3 and 4 record Product 133 as being accepted and purchased as a PDO even though at the cost of the normal price. The discount was received for the cross-sell product, Product 115.

Figure 6.2 presents the repurchase curve for Customer M's Product 133 generated for

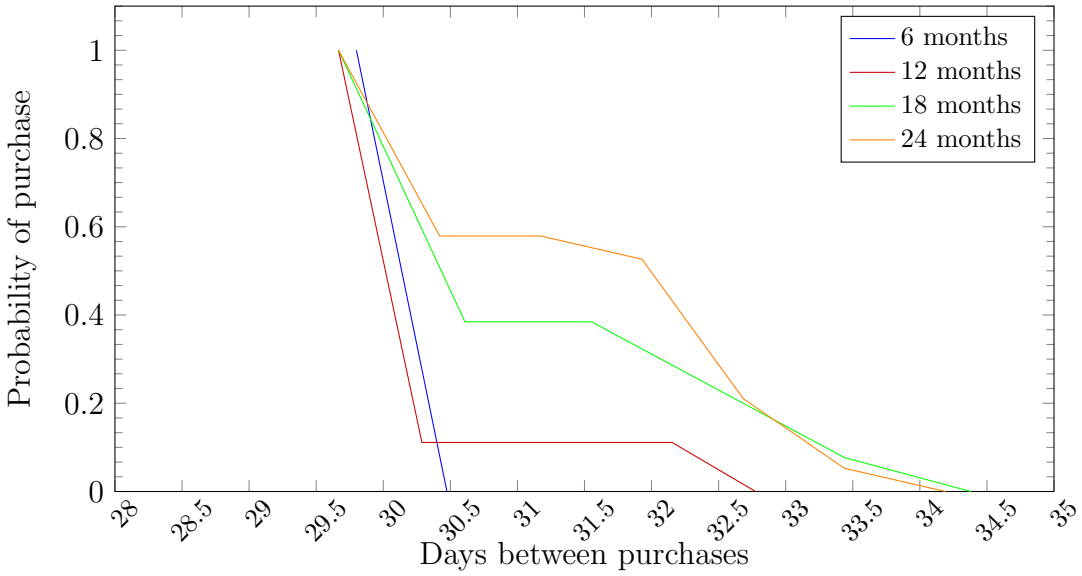


Figure 6.2: Repurchase curves using WRCAA at different time lengths for Customer M's Product 133

different time lengths. During the 12 month time period the periodical purchase pattern was influenced by the interference of the upsell offer in the row between purchase instance 10 and 11 of Table 6.8 and this influence can also be seen in the repurchase curves of the customer-product pair in Figure 6.2. As time passes it is clear to see the repurchase curve improves as a result of more historical behaviour available.

6.5 Chapter 6 summary

This chapter presented a comparison between the two analysis approaches along with the results obtained from the PDO demonstrator using the RCAA and the WRCAA respectively. A specific example was used to illustrate the PDO demonstrator proposing PDOs. The example was used for the PDO demonstrator using the RCAA to propose PDOs as well as the WRCAA. The following chapter concludes this study.

Chapter 7

Conclusion

The results of the proposed model were discussed in the previous chapter. This chapter concludes the discussion of the study. A business model for the service, a summary of the work done in the study and an appraisal of the work are presented. Lastly, suggestions for future work based on the study are provided.

7.1 Business case

This section sheds some light on the business proposition this study has. The researcher proposed a business model for this service by applying the *Business Model Canvas* designed by Osterwalder and Pigneur (2013). The nine building blocks are stated and refined for this initiative and shown in Figure 7.1. The researcher populated the nine building blocks with the focus on this study.

The proposed service suggests a new and alternative way of thinking and conducting business within the retail domain. The relationship between retailers and suppliers is of utmost importance, not only for ensuring products are available on the shelves at reasonable prices, but also ensuring promotional offers are available to customers.

The researcher conducted interviews with individuals working in the retail domain. The conversations were focused on understanding how the relationship between retailers and suppliers works and the decision-making process for discounted offers. Known knowledge was shared and no information regarding retailers was disclosed (Bronkhorst, 2018; Snyman, 2017). From these interviews the researcher could confirm that creating promotional offers can be a stressful task for both the retailers and the suppliers. The relationship between these two parties is tense and often not as one would like it to be. With this new innovation, the retailer-supplier relationship can be strengthened by gaining purchasing behaviour information regarding customers.

The question still stands: *How will a supplier or retailer create revenue by proposing discounted offers?* The proposed system creates a holistic view of customers by including all their purchases from different retailers. The system records transactional data of customers at all the outlets subscribed to this service. The system can thus propose a personalised discount offer (PDO) to a customer at a specific store that is different from where the customer usually buys a specific product. The retail store thus sells a product that would normally be bought at another store at a lower profit margin. These offers are instant and temporary, which expire when the customer leaves the store. The PDOs proposed can also include cross-sell and upsell products which ensures a higher profit margin and can also include a larger volume acquired.

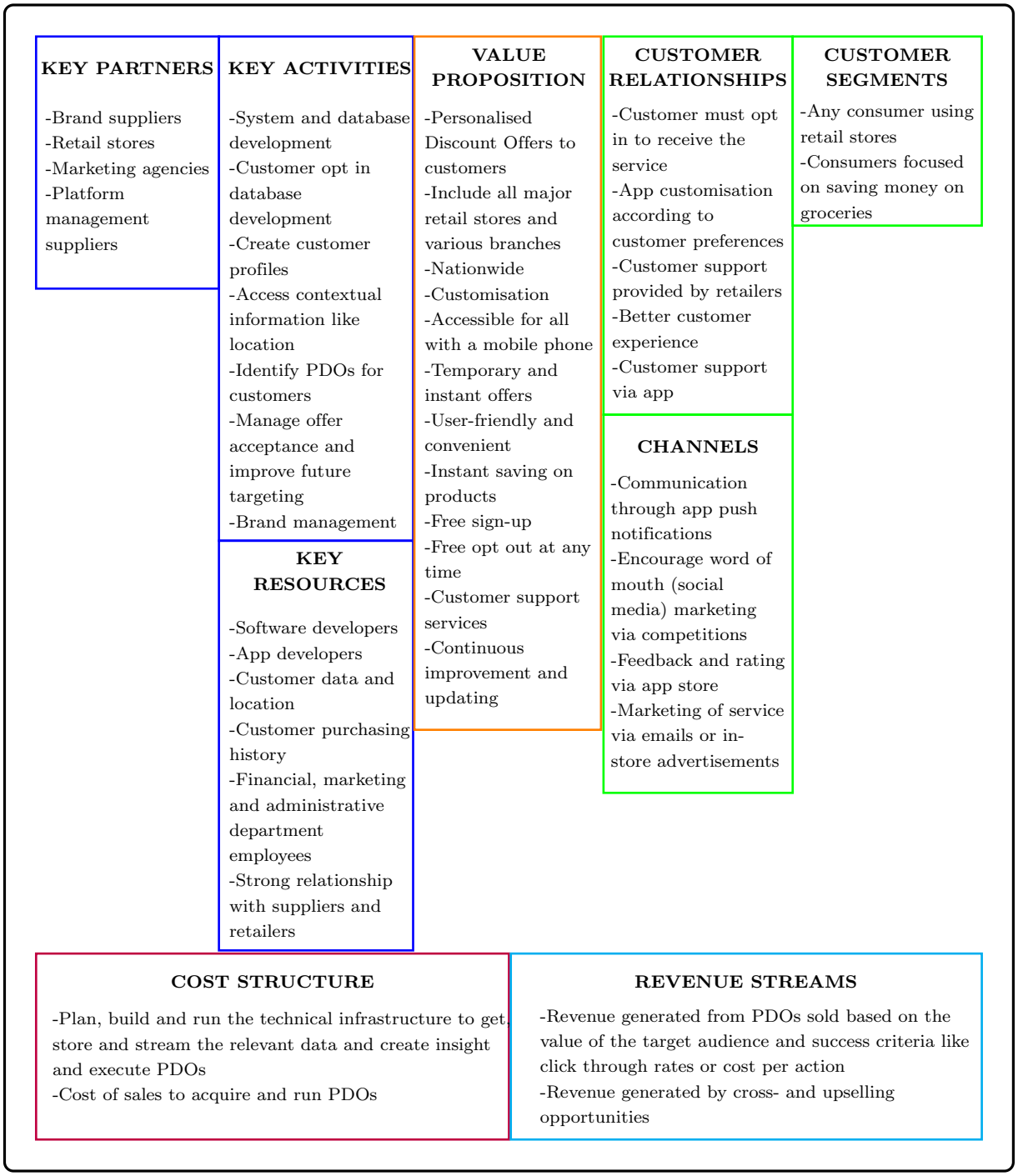


Figure 7.1: Business model canvas, adapted from Osterwalder and Pigneur (2013).

These aspects make the proposed system different from existing loyalty programmes.

This initiative creates an opportunity for retailers to acquire potential customers by improving the customer experience at the alternative outlet by proposing PDOs to them based on their purchasing history. Customer experience is also improved by proposing PDOs via push notifications when entering a store, thus customers do not have to check whether or not they qualify for a PDO. None of the retailers receive information regarding other retailers as the customer information is private and owned by the enterprise hosting this initiative. Using the data gathered, further data analyses can be done in order to gain more information regarding market satisfaction and preferences, which in turn can be provided to the suppliers and retailers.

In order for this innovation to be successful some considerations are necessary. A mobile application is necessary for the system to capture the relevant transactional data of the customers and along with this a platform is required to access relevant informations regarding participating retail outlets, *e.g.* outlet location. This innovation targets customers who have access to mobile devices and data connectivity. Customers must subscribe to this PDO service and be willing to share their location, purchasing behaviour and personal information in order to receive personalised discount offers in return. The application must be used regularly in order to benefit from the PDO opportunities which include cross-sell and upsell offers and customers will be provided the opportunity to opt out at anytime. The retailers must participate in this initiative in order for it to be attainable and also to receive beneficial value from the service.

All enterprises are motivated to create a profit for the business and in order to do so the customer relationship must have the highest priority. The personalisation of offers ensures a higher acceptance rate and by including cross-selling and upselling offers, enterprises can expect an additional revenue stream. The personalisation of discount offers ultimately enhances the customer experience and customer satisfaction, bettering the customer relationship.

7.2 Summary of work done

Chaper 1 introduced the study topic with a background and research assignment. The objectives of the study are stated within this chapter along with a research methodology determining how the objectives would be achieved. A scope of the study and deliverables envisaged are also included in Chapter 1.

This chapter was followed by a literature study undertaken in **Chapter 2**. The literature study provided a broad knowledge foundation to understand the essence of the study. This study included a variety of domains such as Customer Relationship Management (CRM), marketing, cross-selling and upselling, and data analytics. Most of the knowledge areas dis-

cussed in the literature study are related back to the customer and were thus fundamental to the study. CRM focuses on the relationship between customers and enterprises and provides activities to strengthen this relationship. One of the activities included marketing which reflects on the communication between enterprises and customers. Cross-selling and upselling are methods of retaining customers and also an important aspect when looking at proposing offers to customers. The other aspects not directly related to the customer such as system architecture, data analytics and Big Data were important to understand, because they would be used in the study.

Chapter 3 introduced the proposed system by explaining the system architecture. The system architecture was developed using Object-Process Methodology (OPM). OPM was used because of the holistic view it provided of the proposed system. This chapter also included some literature regarding OPM. The architecture of the proposed system was visualised by three Object-Process Diagrams (OPD) accompanied by Object-Process Language (OPL) which was generated for the desired system. The OPL described the system architecture in natural language to make it easier for stakeholders to understand. Lastly, this chapter schematically explained the relationship between the simulator and demonstrator models that were necessary for the completion of the study.

Chapter 4 initiated the design and development of the proposed system starting with the simulator. The simulator was designed to simulate pseudo-customer data showing purchasing behaviour. The reason for simulating the customer behaviour was to overcome ethical issues and to ensure the data are not lacking any information. The simulator was designed using an Extended Entity-Relationship Diagram (EERD). The entities were identified by referring back to the proposed architecture explained in Chapter 3. A theoretical description of the entity–relationships was provided. The data tables of the proposed system were designed by using the data dictionary provided in this chapter. The description of the development of the simulator was done by discussing the population of each data table with data values. The physical data tables were generated and populated using Matlab® and stored in Microsoft® SQL Server, which served as the database for the system. The customer purchasing behaviour was also stored in the database. On completion of Chapter 4, the first objective of the study stated in Chapter 1 was achieved.

Chapter 5 contains the design and development of the PDO demonstrator. The PDO demonstrator was designed to analyse the simulated data generated in order to identify and propose PDOs to specific customers. The PDO demonstrator was also designed to propose cross-sell and upsell products. In order to propose a personalised offer to a customer, one must estimate when the customer anticipated buying the product again. This was done designing the PDO predictor which analysed the historical transactional data of a customer. Four analysis techniques were investigated where two of them were eventually used. These

were the arithmetical average technique, the weighted average technique, a repurchase curve technique followed by a weighted repurchase curve technique. These analysis techniques were compared and evaluated in order to identify the superior analysis approaches that were used in the PDO predictor. From the evaluation, 32 test scenarios where identified to be executed by the PDO demonstrator.

Chapter 6 comprised of a discussion of the results provided by the PDO demonstrator. The PDO demonstrator was capable of proposing PDOs using the identified NPD-analysis approaches. This chapter summarises the evaluation of the PDO demonstrator by introducing the 32 test scenarios. An individual customer journey example was also presented to state the difference between the RCAA and the WRCAA. The PDO demonstrator was capable of proposing PDOs to customers based on their historical purchasing behaviour. Objective 2 was fulfilled by the completion of the work described in this chapter.

A business case was provided in Section 7.1 to shed light on the business proposition of this innovation. An alternative way of proposing discount offers is recommended by proposing personalised offers based on customer specific purchasing behaviour.

7.3 Appraisal of work

This section presents an appraisal of the work done during this study. The researcher found that this topic is applicable within the field of industrial engineering and can contribute to the retail domain. It is key for the reader to understand how this initiative differentiates itself from existing loyalty programmes. The existing loyalty programmes are retail group specific and thus only gather information regarding the current customers. The proposed offers are rarely personalised and in the cases where they are, it is based on frequently bought products and not periodically bought products. No other loyalty programme tries to propose personalised offers to new customers.

The researcher does not propose this initiative to replace any existing discount offer system, since the current systems focus on general public discount offers. This innovation is proposed as an additional revenue stream created by targeting individual customers with personalised offers. The researcher suggests an alternative approach of agreeing upon specialised offers between retailers and suppliers. This could be a challenging process to implement in practice, but can provide a stronger supplier-retailer relationship.

The system was developed using simulated data which might not reflect real life data realistically. The researcher introduced different distributions to ensure the data values are mixed. The acceptance and rejection probability was defined by the researcher, but in reality this probability will be determined from analysing the customer data. The probability of cross-sell and upsell opportunities can be altered by the enterprises and can even be adjusted

for different suppliers and retailers according to an agreement between the respective parties.

This innovation is focused on the retail setting within South Africa and the technology available for the consumers in South Africa. Walgreens in the United States of America partnered with Aisle 411 and Google Project Tango to create a 3D augmented reality to Walgreens. Aisle 411 helps a customer search and map products to where they are located on the shelf, whereas Project Tango can determine a user's location within the store (Aisle411 and Google Project Tango and Walgreens). This innovation proposes more a game-like shopping experience and is limited to a Tango device and Walgreens store. This innovation does not show any personalised discount offers based on specific customer transactional history.

So, the proposed system will ideally be compatible on any device and focuses on more than one retailer and supplier. The essence of the developed system is that it proposes PDOs to customers based on their transactional history. The value of the work lies in the analysis of the transactional history data of a specific customer.

7.4 Future research

This study opens avenues for future work. This includes investigating other techniques for analysing specific product repurchasing intervals to identify suitable instances to propose PDOs. It will be beneficial to test the PDO demonstrator on actual customer data gathered within South Africa. It is important to investigate the technical difficulties of implementing this initiative in South Africa and determining the cost of the development and implementation of a real system. The implementation of the proposed system will require experts from other domains, *e.g.* marketing. The prospect of influencing potential customers and retailers is one of the many exciting, challenging aspects of industrial engineering. If the system is successfully implemented the next step would be to implement the option of proposing PDOs to customers as the customers pass the PDO product in the aisle.

7.5 Chapter 7 summary

This chapter concludes this study with a business case which describes the business proposition of this innovation. This is accompanied by a summary of the work done and an appraisal thereof. The study is concluded with an outline of suggestions for possible future work.

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